FATIGUE EFFECT ON TASK PERFORMANCE IN HAPTIC VIRTUAL ENVIRONMENT FOR HOME-BASED REHABILITATION

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By

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ABSTRACT

Stroke rehabilitation is to train the motor function of a patient's limb. In this process, functional assessment is of importance, and it is primarily based on a patient's task performance. The context of the rehabilitation discussed in this thesis is such that functional assessment is conducted through a computer system and the Internet. In particular, a patient performs the task at home in a haptic virtual environment, and the task performance is transmitted to the therapist over the Internet. One problem with this approach to functional assessment is that a patient's mind state is little known to the therapist. This immediately leads to one question, that is, whether an elevated mind state will have some significant effect on the patient's task performance? If so, this approach can result in a considerable error.

The overall objective of this thesis study was to generate an answer to the aforementioned question. The study focused on a patient's elevated fatigue state. The specific objectives of the study include: (i) developing a haptic virtual environment prototype system for functional assessment, (ii) developing a physiological-based inference system for fatigue state, and (iii) performing an experiment to generate knowledge regarding the fatigue effect on task performance. With a limited resource in recruiting patients in the experiment, the study conducted few experiments on patients but mostly on healthy subjects.

The study has concluded: (1) the proposed haptic virtual environment system is effective for the wrist coordination task and is likely promising to other tasks, (2) the accuracy of proposed fatigue inference system achieves 89.54%, for two levels of fatigue state, which is promising, (3) the elevated fatigue state significantly affects task performance in the context of wrist coordination task, and (4) the accuracy of the individual-based inference approach is significantly higher than that of the group-based inference approach.

The main contributions of the thesis are (1) generation of the new knowledge regarding the fatigue effect on task performance in the context of home-based rehabilitation, (2) provision of the new fatigue inference system with the highest accuracy in comparison with the existing approaches in literature, and (3) generation of the new knowledge regarding the difference between the individual-based inference and group-based inference approaches.

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DEDICATE TO MY GRANDMOTHER

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Chapter 1 Introduction

1.1 Home-based rehabilitation

In 2006, the World Health Organization (WHO) (2006) reported that the heavy burden associated with neurological diseases causes a scarcity of neurological services and resources in the medical system worldwide. Stroke is one of the leading neurological diseases that cause death and disability in Canada (CIHI, 2006). Stroke causes the functional loss at one side of body. In 30% to 60% of stroke patients, the affected upper limb remains without function for 6 months after acute stroke; only 5% to 20% demonstrate complete functional recovery (Kwakkel et al., 2003). Therefore, there is a continuing need for rehabilitation to retrain the functional state on the affected upper limb after acute stroke. In this case, home-based rehabilitation is carried out in such a way that the patients and clinicians are separated geographically. As a follow-up treatment, the home-based rehabilitation is very useful to patients who live far away from the clinical center and cannot easily access rehabilitation services.

1.2 Motivation

This study is motivated by how human mind state may significantly affect task performance in the context of home-based rehabilitation. Note that in this thesis, home-based rehabilitation is done with a haptic virtual environment system. Such a system consists of a haptic device, patients, and virtual environment and is a typical human-machine-environment (HME) system. In the study of HME, there is an issue regarding how human mind state affects task performance. This issue may also be called mind state effect. When patients perform the task-oriented functional assessment on a haptic system, their mind state may affect task performance. As such, task performance information, brought to the clinician's attention, may not only represent the task performance contributed by the functional state of upper limb but also by the elevated mind state. Colle et al. (2006) reported that fatigue is a common complaint after stroke, and occurs in 39-72% of stroke survivors. Therefore, the first question in this thesis study is: **does an elevated fatigue state significantly affect the task performance in the context of home-based rehabilitation?**

Human cognitive fatigue can only be inferred from cues. The inference system is a mapping between cues and fatigue state. There are two categories in terms of source of the cues: individual-based inference and group-based inference. The individual-based inference gets cues from one individual to be inferred, and the cues information is then used to infer that individual's mind state. The group-based inference gets cues across different individuals, and the group cues information is then used to infer an individual's mind state. In group-based inference, the person to be inferred may not even necessarily be in the group. Therefore, the second question in this thesis study is: **whether there is any significant difference between the individual-based inference and group-based inference?**

In general, the contemporary literature in rehabilitation has not provided sufficient knowledge to answer the aforementioned two questions; a detailed review of literature is provided in the next chapter. The motivation of this thesis is to generate knowledge to answer the two questions described above, and is to advance home-based rehabilitation technology for stroke patients.

1.3 Objectives

There are three specific objectives defined for this thesis study:

Objective 1: Build a haptic virtual environment prototype system for functional assessment.

In the context of home-based rehabilitation, the haptic virtual environment prototype system for functional assessment is built for the purpose of conducting experiments. The generated prototype system is restricted to the assessment of wrist coordination function only.

Objective 2: Build a fatigue inference system to infer fatigue from physiological cues.

To study the fatigue effect in the laboratory environment, there is a need to build a fatigue inference system to infer the elevated fatigue state. In achieving this objective, improvement of inference accuracy will also be taken care of in the context of a vast amount of literature about fatigue inference in various other applications.

Objective 3: Design and conduct experiments to generate knowledge for the research questions described in Section 1.2.

There are three specific purposes related to this objective: (1) to validate the fatigue inference system, (2) to study the effect of fatigue on task performance in the haptic system, and (3) to study the difference between individual-based inference and group-based inference approaches.

1.4 Organization of the thesis

This thesis is comprised of six chapters. The subsequent chapters are organized as follows:

Chapter 2 will present a background of the knowledge pertinent to this research and review the literature to further confirm the significance of the proposed objectives.

The design of the haptic virtual environment system for functional assessment will be discussed in Chapter 3. The experimental validation of the virtual environment system will also be presented.

Chapter 4 will present the architecture of a fatigue inference system. Both disadvantages and advantages of cues to infer fatigue will be discussed. The methodology and procedure will also be discussed to build the fatigue inference system, aiming to improve the accuracy of the inference.

Chapter 5 will present the experimental study of how fatigue affects task performance in the context of rehabilitation and of the difference between the individual-based inference and group-based inference approaches. The validation of the developed inference system will also be presented.

Chapter 6 will conclude this thesis by presenting the result of the research, discussing contributions of the research, and proposing the future work.

Chapter 2 Background and Literature Review

2.1 Introduction

This chapter presents literature review pertinent to the objectives as defined in Chapter 1 of the thesis. Section 2.2 discusses research on the haptic system for functional assessment of upper limb. Section 2.3 presents research on the machine-learning technique to infer cognitive state, especially fatigue. Section 2.4 discusses the emotion or cognitive effect on task performance in a general Human-Machine-Environment (HME) situation. At the end, there is a revisit of the research objectives defined in Chapter 1 to further justify the need of the proposed research and its nature.

2.2 Haptic system and its potential use for functional assessment of upper limb

2.2.1 Functional assessment of upper limb in clinical setting

Functional assessment of upper limb is task-oriented. In clinical settings, the therapist asks the patient to perform a set of tasks and observes the task performance of the patient. Task performance has close correspondence with the impairment in a patient's motor behavior (i.e., function loss). Therefore, through examining patient's task performance information, the therapist is able to assess the patient's function loss. Figure 2-1 presents the schematic of functional assessment in a clinical setting, which is self-explanatory.

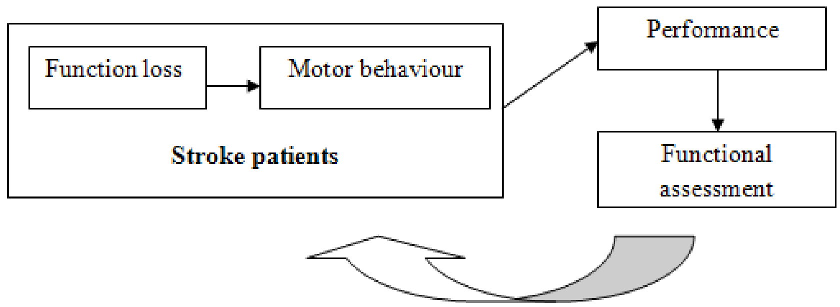

Figure 2-1: Functional assessment in clinical setting

Based on the author's observation at the City Hospital at Saskatoon, the occupational therapists assess the function loss in terms of the recovery stages. For a particular stage, therapists assess the function loss at the current stage to examine whether the patient can go to the next stage. If the patient's performance was not bad, then the therapists would assess the function loss at the next stage. For instance, for a patient at Stage 3, the therapist will examine whether his or her wrist extension is larger than the ½ range, which is a typical performance characteristic of the patient at Stage 3. For this purpose, the therapist subsequently asks the patient to do the test item associated with the next stage, at which finger movement and coordination manner are emphasized.

Twitchell (1951) observed and described motor recovery through the assessment of synergistic patterned movements for patients after stroke. Following his work, Brunnstrom (1970) suggested classifying and describing the process of recovery by six stages in the hemiplegic arm and leg. Based on Brunnstrom's six stage theory, the Fugl-Meyer Assessment (FMA) was developed as an evaluative measurement of motor impairment (Fugl-Meyer et al., 1975). The test items with the corresponding procedure in FMA are specific to the function loss based on Brunnstrom's six stage theory. The functional assessment is further divided into 5 domains: motor, sensory, balance and coordination, motion range of joint and joint pain. For the upper limb section, there are 33 items for functional assessment in terms of motor function (e.g., shoulder, elbow, hand, and wrist). Gowland (1990) relates the test items of the FMA to Brunnstrom's six stage theory. For a specific recovery stage, the performance characteristics of upper limb (e.g. arm and hand) are shown in Figure 2-2. Figure 2-2 illustrates the motor behavior in upper limb at 1 to 4 stages of motor impairment. As long as a patient is able to perform the test items fully at one stage, he or she goes to the next recovery stage.

Arm	
1	Not yet stage 2
2	Resistance to passive abduction or elbow extension
	Facilitated elbow extension
	Facilitated elbow flexion
3	Touch opposite knee
	Touch chin
	Shoulder shrugging >½ range
4	Extension synergy then flexion synergy
	Shoulder flexion to 90°
	Elbow at side, 90° flexion: supination then pronation
Hand	
1	Not yet stage 2
2	Positive Hoffman
	Resistance to passive wrist or finger extension
	Facilitated finger flexion
3	Wrist extension >½ range
	Finger/wrist flexion >½ range
	Supination, thumb in extension: thumb to index finger
4	Finger extension then flexion
	Thumb extension >½ range then prehension
	Finger flexion with lateral

Figure 2-2: Motor behavior at Brunnstrom's stages of function loss (Gowland, 1990)

The FMA assesses the function loss through single-joint functional tasks. Other functional assessments such as Wolf Motor Function Test (WMFT) and Activities of Daily Living (ADL) focus on the combinations of function losses through the multiple-joint functional tasks. The WMFT is the time-based and multiple-joint function assessment (Wolf et al., 2001). The ADL is a multiple-joint functional assessment, in which the test items are closer to daily life activities. Examples of the test items are eating, dressing, bathing (Wiener et al., 1990). These test items consist of the combinations of single-joint functional tasks in the FMA.

2.2.2 Haptic system and haptic-based virtual environment

2.2.2.1 Haptic system

The term "haptics" refers to a sense of touch. When a human touches a real or virtual object, forces are imposed on the human body. The haptic system consists of the human, haptic device, and environment. In general, the haptic system gives humans tactile and kinematic sensory information when they interact with an environment. Figure 2-3 further illustrates the haptic interaction between the human and machine. The figure shows that humans sense the force and control the motor variable in the haptic system.

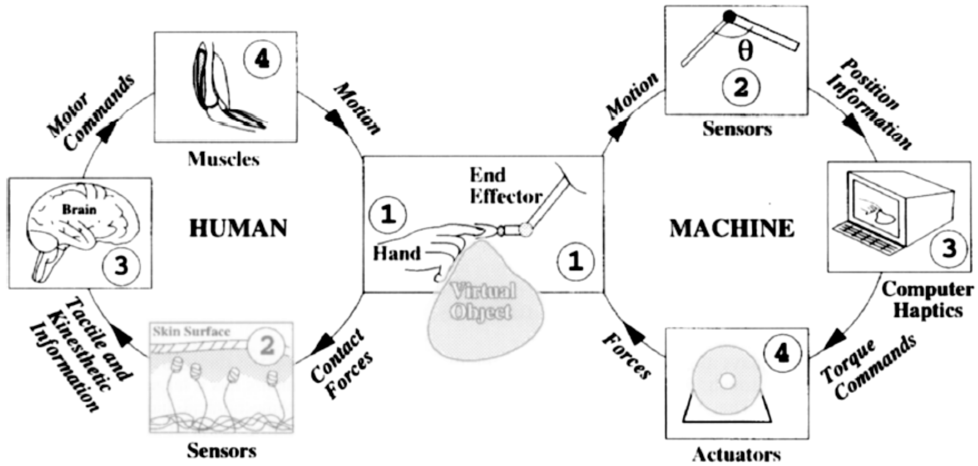

Figure 2-3: Haptic interaction in HME (Srinivasan and Basdogan, 1997)

2.2.2.2 Virtual environment

Virtual environment (VE) refers to interactive simulations which present opportunities to humans to interact with the virtual objects that appear sound and have offered humans a similar feeling to real world objects (Schultheis and Rizzo, 2001). When the users interact with a virtual object, they can feel the real object through their sensors including vision, hearing, and touching. The key concept of virtual environment is immersion and presence. The immersion means self-representation of users in a virtual environment. The immersion leads to presence of users in a virtual environment. Steuer (1992) pointed out that a virtual environment is a simulated environment in which the users experience tele-presence. More immersive virtual environments provide users with the perception of “being there” in the environment, while less immersive virtual environments provide little sense of the presence.

For **a fully immersive virtual environment**, the users have a strong sense of the presence. A tracking system and a head-mounted display (HMD) sense the position and orientation of the users' head (Sanchez and Slater, 2005). HMD is a small monitor mounted in front of each eye. The users interact with a virtual environment by head movement. The cave automatic virtual environment (CAVE) system was developed at the University of Illinois at Chicago, and the system provided a room-sized, three-dimension (3-D) video and audio virtual environment (Neira et al., 1993). In CAVE system, the environment is projected on a concave surface to create the sense of immersion. A video capture system, namely, the interactive virtual reality exercise (IREX) system was developed by Weiss et al. (2004). The movements of the users' body were captured by IREX. The users view themselves or an avatar in the scene on a computer screen.

For a **less immersive virtual environment**, users feel little sense of the presence. The users interact with the virtual environment with different degrees of immersion with or without the interface device such as haptic device. The haptic-based virtual environment will be discussed in the next section.

2.2.2.3 Haptic-based virtual environment

The haptic-based virtual environment is a less immersive virtual environment. The movement of the haptic device corresponds to the movement of a virtual stick or ball making the degree of immersion at the hand in the virtual environment. In a haptic-based virtual environment, the haptic device gives a positional input to the virtual environment and provides a force feedback to the users. Figure 2-4 illustrates the haptic-based virtual environment developed by Dreifaldt and Lovquist (2006). In the beginning, the users move the haptic stick. At the end, he or she can see a ball pointer moving the screen and feel the sense of touch in the virtual environment when the ball hits the wall.

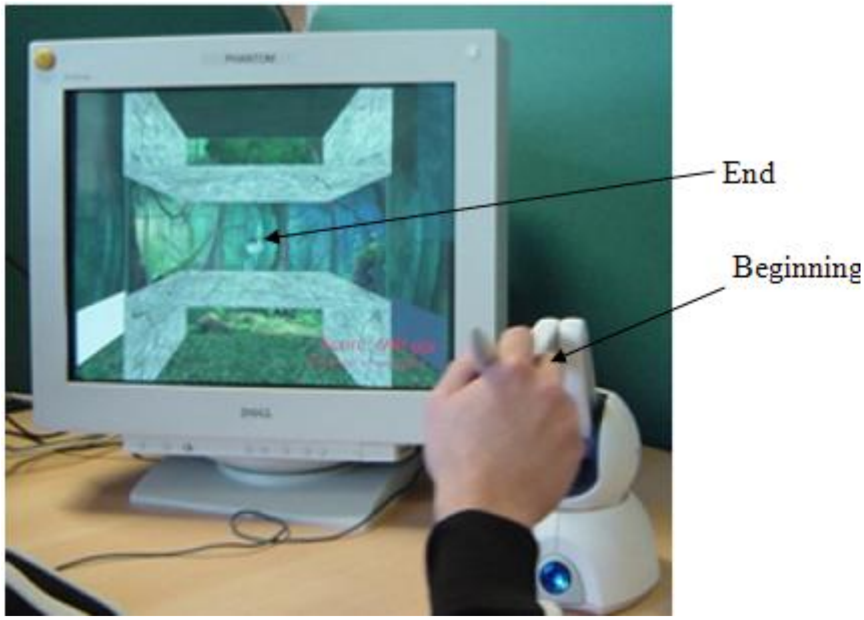

Figure 2-4: Scene of a haptic-based rehabilitation system (Dreifaldt and Lovquist, 2006)

Previous work in Bardorfer's group showed some labyrinths games created in the virtual environment and conceived a new upper limb analysis test on the functional assessment test by using PHANTOM Premium haptic device (Bardorfer et al., 2001). In their system, by measurement of the position of and forces on a stylus in the virtual environment, the clinician was able to characterize the motor behavior of patients with neurological diseases. Figure 2-5 illustrates the simulated task in the virtual environment in Bardorfer et al. (2001). In this figure, the subjects manipulated the virtual ball by a haptic device to pass the labyrinth. The performance parameters such as speed, time, and movement of upper limb are measured in the virtual environment.

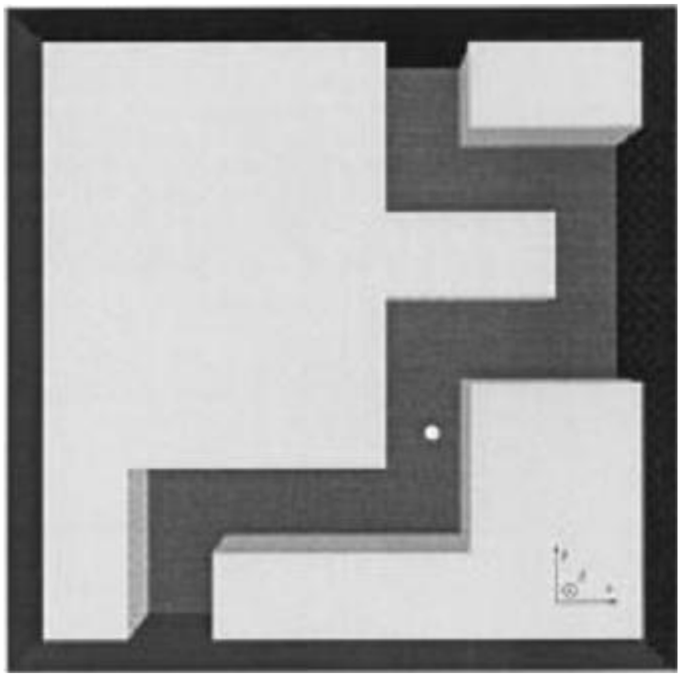

Figure 2-5: Labyrinth task developed by Bardorfer et al. (2001)

Broeren et al. (2002) proposed an assessment device for stroke patients incorporating both virtual environment and haptic device (PHANTOM Omni). In the virtual environment, several parameters including time, speed, and movement of the upper limb were extracted and evaluated. The study presented the functional assessment for motor skills of the upper limb. The result showed that the performance in the patients' group appeared to be different from the reference group. The study demonstrated that the haptic-based virtual environment enables the individual to perform the tasks with sensory feedback (e.g., capability to grasp). When the users manipulate the objects in the virtual environment, it is possible for therapists to track movements for further analysis.

Other examples of the haptic-based virtual environments for rehabilitation are Cyber Force (Kayyali et al., 2007) and Cyber Glove (Adamovich et al., 2005). These systems are proposed for haptic-based exercises for finger movements and strength increment. Figure 2-6 illustrates the instrumentation of the Cyber Force system.

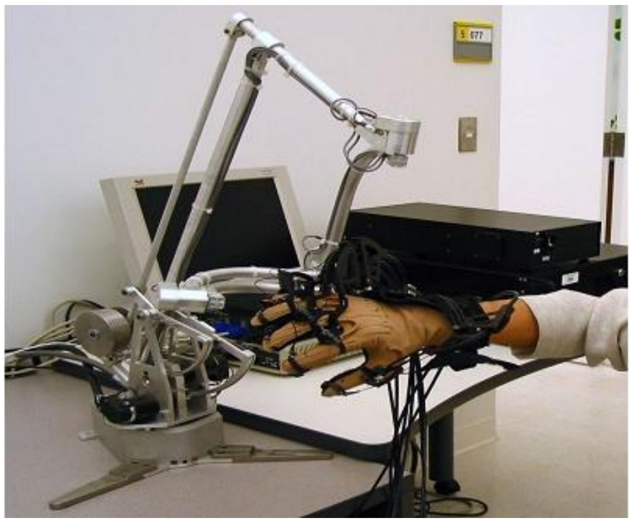

Figure 2-6: Instrumentation of Cyber Force system developed by Kayyali et al. (2007)

The virtual environments created by Cyber Force are more immersive, because they can reflect the position and orientation of each finger. Figure 2-7 illustrates the virtual environment created by the Cyber Force. The figure shows that the subject was doing exercises to lift an object on the shelf in the virtual environment.

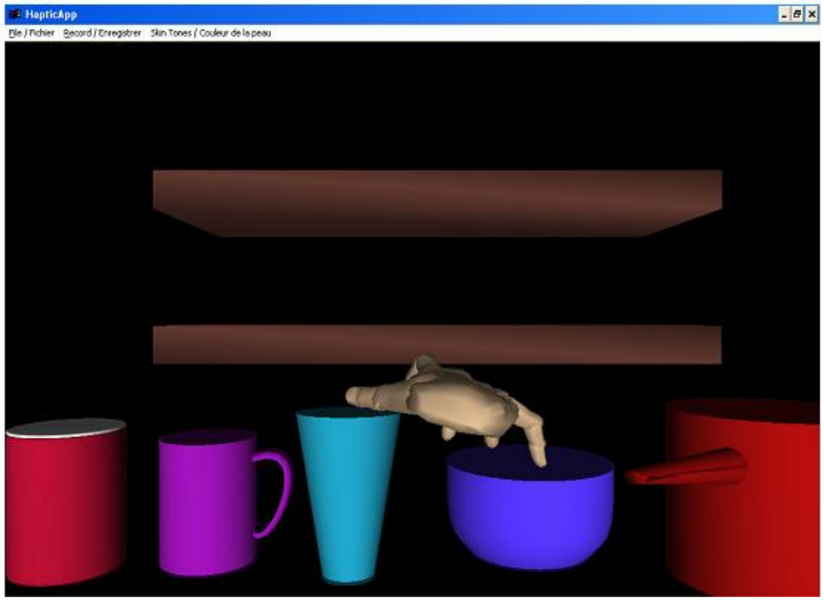

Figure 2-7: Virtual environment of Cyber Force system by Kayyali et al. (2007)

In conclusion, the haptic system has great potential in rehabilitation to monitor and track head, arm, and leg movements with force load. Most importantly, the virtual environment leads to tele-presence of the users. A detailed review of using virtual environment in stroke rehabilitation was presented by Holden (2005) and Henderson (2007). The tele-rehabilitation concept was proposed by Cooper et al. (2001). Under this concept, functional assessment can be carried out remotely in such a way that the patients and clinicians stay in geographically different locations, and they communicate with each other through the Internet.

2.3 Inference of cognitive fatigue state

2.3.1 Inference and inference system

Human cognitive fatigue state can be inferred from cues or signals. The inference system is a mapping between the cues and fatigue state. In literature, there is no convinced first principle available to construct such a mapping, so the mapping can only be established through empirical learning. Learning needs resources which are historical data about the relationship between cues and fatigue state. The historical data may be called ‘training data’ in the context of a popular inference technique called artificial neural network (ANN). This thesis will use this term throughout for whatever inference system techniques.

Training data has two dimensions: person and time. The person dimension refers to the number of persons whose cues and fatigue states are acquired, and the time dimension refers to the number of time spans at which a person’s cues and fatigue states are acquired.

There are two paradigms of learning with respect to this nature of training data: individual-based learning and group-based learning. For individual-based learning, a person’s past data along the time dimension is the training data which will be further used to infer that particular person’s fatigue state. For group-based learning, a group of persons’ data are training data which will be used to infer a person’s fatigue state (that person may not necessarily belong to that group).

Three elements are important in developing an inference system, that is, (1) training data and the way to acquire them, (2) the structure of a mapping and the way to determine the structure, and (3) the parameter of the mapping and the way to determine the parameter. Further, training data can be categorized into two types: supervised training data (cues and fatigue state are both available) and unsupervised training data (cues are available only). These elements are dependent on one another. For instance, the way to determine the mapping parameter with the supervised training data is quite different from the way to determine the mapping parameter with the unsupervised training data.

In the MIT media group, Picard et al. (2001) proposed an emotion inference system to map physiological signals to different emotional states. The physiological signals are a person's muscle activity, skin conductance, heart rate variation, and respiration rate. Figure 2-8 illustrates the structure of the inference system. The structure of the inference system consists of three layers: input, hidden, output. In their work (Picard et al., 2001), a supervised learning algorithm called K-nearest neighbor (KNN) was employed to classify the emotion states. The physiological signals taken as supervised data were labeled by the experimenter in terms of emotional states. Their study demonstrated that there are some relations between the physiological signals and emotional states. However, there is no precise magnitude to label the emotional states in physiological signals. The result of their study showed that the accuracy of the inference system achieved to 81% to classify 8 emotion states.

The research group of Nasoz et al. (2003) developed an emotion inference system to recognize the emotional states as well. The training data was heart rate, skin temperature, and skin conductance. The training data was stored in a three dimensional array. These three dimensions are (1) the participants in the experiment, (2) the emotion classes being elicited, and (3) the physiological signals. Three algorithms were employed to determine the weights: (1) KNN, (2) discriminate function analysis (DFA), and (3) Marquardt back propagation (MBP). Their research elicited emotions by the scenarios in the different films. The inference system is actually to map the physiological signals to different scenarios. The validation of the elicited emotion corresponding to the scenarios can be easily challenged with their work.

Mandryk and Atkins (2007) developed a fuzzy inference system to map physiological signals to the emotional experience when users were playing games. The training data is galvanic skin response (GSR), heart rate, and electromyography (EMG). Figure 2-9 illustrates the structure of the fuzzy inference system. The fuzzy inference system consists of input, output, membership functions, and if-then rules. In a fuzzy inference system, if-then rules determine the weighting factors, which are the parameters of the model. In their approach, the if-then rules were developed by a previous study about emotion (Russell et al., 1989), and these expert rules were the key point to influence the output of the fuzzy inference system. However, the training data of the expert rules from the other literature may not adapt to the subjects in their situation.

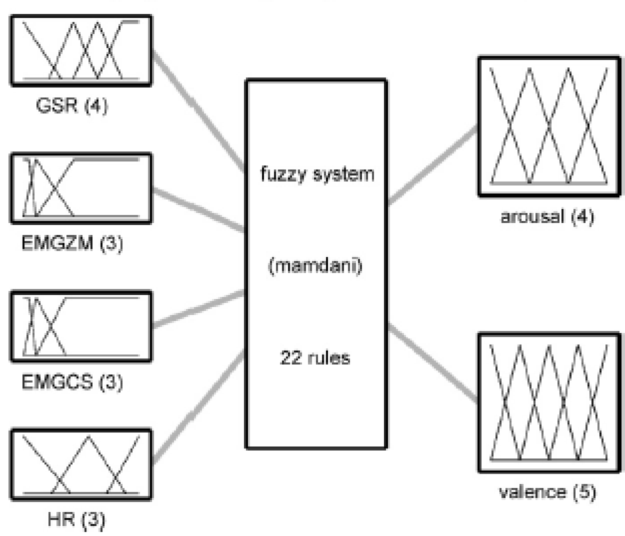

Figure 2-8: Structure of the fuzzy inference system in (Mandryk and Atkins, 2007)

2.3.2 Acquisition of training data for fatigue

According to the preceding discussion, there is a need of training data in order to develop a fatigue or any mind state inference system. For both supervised and unsupervised training data, a kind of label to describe the order or magnitude of fatigue state has to be defined or designed. There are three kinds of such labels in literature. In the following, the word 'measurement' is used instead of the word 'label' for the compatibility with other physical attributes in a conventional use.

Subjective measurement

It requires the subjects to rate their level of fatigue through questionnaires or interviews. Subjective rating can reflect the inherent interpretation of fatigue. In the literature, subjects seem to be bad at self-reporting, because the description between the levels of fatigue is too vague (Yang et al., 2008). In addition, subjective rating only generates the data when a question is asked. Therefore, it interrupts the subjects in performing a task in HME. Most importantly, the subjects may not give them the answer to represent their true feeling in the laboratory environment. The rating scale to fatigue inference includes: Rating Scale Mental Effort (RSME) developed by Zijlstra (1993), NASA Task Load Index developed by Hart and Staveland (1988), and a self-assessment tool for mental fatigue published by Johansson et al. (2010). Subjective rating can reflect the human's attribute to interpret the fatigue. The problem is, however, that each individual has his or her own opinion about fatigue.

Performance-based measurement

It asks the subjects to perform cognitively demanding tasks and analyzes the task performance responding to elicited fatigue states. There is evidence which shows a significant decline of cognitive performance due to an elicited fatigue. However, the decline of cognitive performance may also be affected by other factors such as physical fatigue or human intelligence. In literature, there are several proposed tasks for performance-based measurement, which include Paced Auditory Serial Addition Test (PASAT) developed by Cook et al. (2007) and Linden el al. (2003) and Auditory Vigilance Task (AVT) by Shen et al. (2008). In these tasks, a standard procedure was also developed to perform the cognitive tasks. The performance-based measurement has a sense of magnitude, i.e., task performance score. Such a score can be related to a label of fatigue. The label of fatigue is further dependent on the way of eliciting fatigue, which is inherently subjective.

Physiology-based measurement

It can be acquired in real-time and can be quantitatively measured, e.g., heart rate. However, it is difficult to label physiological signals to the magnitude of fatigue state. In addition, a single marker for fatigue does not exist at all, though multiple physiological signals may be able to represent distinct patterns associated with fatigue or in general mind state. In fact, physiological signals have never been used alone, and they need to work with subjective measurement of the subjects, for example as in the work of Lin and Cai (2009) or with a subjective manner defined by the experimenter as in the work of Shen, et al. (2008).

Another challenge in getting the training data for mind state inference is the elicitation of elevated mind states, the nature of which is to devise scenarios. Human subjects are supposed to interact with the scenarios such that the mind states of the subjects vary with respect to the scenarios. There are two kinds of the elicitation methods reported in literature, namely (1) simulated scenario, and (2) cognitively demanding task.

Regarding the method of simulated scenario**,** Healy et al. (1999) conducted a study to detect the stress level. In their study, the subject's stress was elicited by daily driving tasks. These driving tasks provide a real world situation where the events of different stressful levels occur. Nasoz et al. (2010) and Yang et al. (2008) used a simulated driving condition to elicit the fatigue in the laboratory environment. In the both scenarios, created by virtual reality, the participants drove on a straight and long road with a constant speed for a long time. However, such scenarios may cause physical fatigue such as drowsy and sleepy, which challenge the genuine mental fatigue elicitation.

Regarding the method of cognitively demanding tasks, Linden et al. (2003) induced fatigue by using cognitively demanding tasks. They showed that participants doing cognitive tasks significantly increased their mental fatigue compared to the control group based on the subjective rating. Cook et al. (2007) used the cognitive task called PASAT, which requires the participants to attend auditory information and retrieve it from their working memory system. As a result, the cognitive tasks involving attention and memory demand significantly more brain activity than less cognitively demanding tasks. Shen et al. (2008) designed an auditory cognitive task to elicit cognitive fatigue state based on biological mechanisms. The results showed that there was a significant change in mental effort between cognitive tasks and non-cognitive tasks.

2.4 Mind state effect on task performance

Since there is not much related work on mind state effect on task performance in the area of rehabilitation, the following discussion extends the literature to some other HME systems – in particular driving.

There are several studies on the emotional or cognitive effect on performance in a driver-vehicle-environment (DVE) system. In a DVE, the driver plays a role of supervising, controlling, actuating, and sensing. The driver handling behavior is reflected by two aspects: cognitive state and driving performance. Cognitive effects and manipulation skills may contribute to the human errors in driving. Further, human errors lead to accidents. Lin et al. (2005) model the mental workload to the driver's handling behavior in a DVE system. Figure 2-10 illustrates the structure of the DVE system. The experiment was performed in three road conditions and the result of the experiment was compared with a simulated DVE system. The simulation results showed a good agreement with the experimental results. Mehler et al. (2009) studied the impact of cognitive workload on the performance in young adult drivers. In the study, the workload was manipulated by using increasing difficult levels of the cognitive task. The experiment was carried out to compare the driving performance at the lower and higher levels of the added workload. As a result, there was a significant decrease in the simulated driving performance with increase of workload.

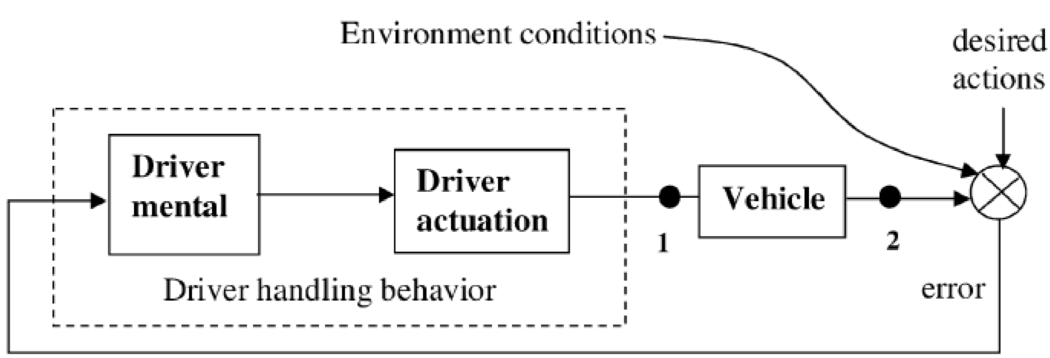

Figure 2-9: The structure of the DVE system in (Lin et al., 2004)

2.5 Conclusion with discussion

There is a great potential to use haptic-based virtual environment for functional assessment of upper limb. The haptic device provides an effective mean to deliver a sense of touch for the users and to track the movement of upper limb in the virtual environment so that the users' upper limb function can be assessed. The haptic-based or haptic virtual environment is relatively simple and cheap. The literature review has well supported the significance of research on objective 1, proposed for this thesis study (see Chapter 1).

The inference system for mind state such as fatigue is essentially a machine learning process. In fatigue state inference or in general mind state inference, the most difficult task is to obtain training data, which is further divided into (i) getting the label and (ii) eliciting the fatigue state. For (i), a dilemma really exists in the degree of semantics and the degree of objectivity. A subjective labeling approach will certainly achieve the highest degree of semantics (e.g., the meaning of 'very' fatigue) but its objectivity is perhaps the lowest. Physiological and task performance labeling approaches will certainly achieve the highest degree of objectivity but the degree of semantics (e.g., fatigue) they are supposed to represent is low. For (ii), a solution is to take the individual-based inference strategy, as first described in Lin (2006). In this thesis, the approach which was taken is to use task performance score as a fatigue label and physiological signals as cues. Furthermore, the individual-based inference strategy was investigated as opposed to the group-based inference strategy. In short, research proposed for objective 2 defined in Chapter 1 should be significant to the field of mind state inference.

Finally, research on objective (3) is totally new in the context of the contemporary literature in rehabilitation. The outcome of the research will be useful to the general field of cognitive science and engineering.

Chapter 3 A Haptic Virtual Environment System for Functional Assessment

3.1 Introduction

This chapter discusses a haptic virtual environment system for functional assessment of upper limb especially wrist coordination. The difference of the development in this thesis as compared with the work of Bardorfer et al. (2001) is that the present design follows a more rational design approach, in particular the axiomatic design theory (ADT) (Suh, 1990). The detailed description of ADT is presented in Appendix A. ADT advocates (1) to understand the requirement and (2) to conceive the design that meets the requirement in an uncoupled or decoupled manner. A preliminary assessment of the effectiveness of this virtual environment system is also presented. Following the ADT, the first step of design is to define the functional and constraint requirements, and the second step is then to determine the design parameters that meet the requirements. Applying the ADT to the problem has led to the following developments: (1) the requirement definition and analysis (in Section 3.2), (2) the task determination in the haptic virtual environment (in Section 3.3), and (3) the detailed design of the haptic virtual environment – task implementation (in Section 3.4). In Section 3.5, an evaluation of the developed haptic virtual environment system is presented. A conclusion is presented in Section 3.6.

3.2 Requirement definition and analysis

As opposed to the design of the haptic virtual environment (HVE) system by (Bardorfer et al. 2001), this study followed a more systematic design procedure, i.e., ADT (Suh, 1990). According to ADT, the functional requirement (FR) of a device system should be defined independently. As a common sense of design model, the functional requirements along with constraint requirements come from customer needs.

In the case of HVE, the customer here is the therapist who conducts functional assessment of stroke patients. The therapist requires assessing the functions of the affected upper limb in accordance with Brunnstrom's six stage theory. This theory classifies the function loss of stroke patients against the stage; in particular, a lower stage corresponds to more function losses. Further, the relationship between the stage and the type of function loss can be represented by the following matrix.

$$\begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_5 \\ S_6 \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ 0 & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & & \vdots \\ 0 & \cdots & 0 & A_{6n} \end{bmatrix} \begin{bmatrix} FL_1 \\ FL_2 \\ \vdots \\ \vdots \\ FL_n \end{bmatrix} \tag{3-1}$$

where s_i: stage i; FL_i: function loss type i; A_{ij}: correspondence number ($A_{ij} = 0$ means that a function loss of type j does not occur to the patient at stage i; $A_{ij} = 1$ means that a function loss of type j does occur to the patient at stage i); n: the total number of types of function loss.

In a clinical setting, two well defined test standards, namly FMA (Fugl-Meyer et al., 1975) and ADL (Wiener et al., 1990), are commonly used to guide functional assessment, which were desribed in Section 2.2.1, respectively. These standards are based on Brunnstrom's stage theory. The therapist picks test items from these standards, and then a patient performs on the test item. Through inspection of the patient's test result, the therapist determines whether a paticular type of function loss presents to the patient and the degree of function loss of that type of function in case that the function loss of that type does present with the patient.

It is futher noted that the diagonosis of the patient to a particular stage is based on a notion which may be called characteristic types of function loss corresponding to a particular stage. That is to say, each stage has characteristic types of function loss. For instance, the wrist coordination function is a characteristic type of function loss at Stage 6. However, this type of function loss also appears in patients at downward stages (e.g., Stage 5 and Stage 4, etc.). Note that the higher the number of stage, the better function of upper limb. The practice with the "downward" function loss concept represents the fact that (1) motors and functions are coupled, (2) function loss at a lower stage is more serious than that at an upper stage, and (3) types of function loss at lower stages cover those at upper stages. This last fact is consistent with the matrix representation of Equation (3-1).

In this thesis study, the charcteristic function loss corresponding to Stage 6 was focused on. The functional requirements and constraint requirements of the task in HVE for this purpose are defined as follows:

Functional requirement (FR)

FR1: To examine the wrist extension at elbow 0 degree.

FR2: To examine the wrist coordination.

Constraint requirement (CR)

CR1: To lift up the hand while keeping the arm straight.

CR2: To move the hand around while keeping the elbow bent and arm at rest.

3.3 Conceptual design of tasks

The approach of ADT helps the designers to transform the customer needs into FRs with CRs and then to transform them into design parameters (DPs) (Li et al., 2010). In the case here, a particular task and the way to perform the task are meant for the DPs in the context of ADT. The goal of conceptual design is to map the FRs with CRs to DPs with an uncoupled or decoupled manner according to Axiom I of ADT (Suh, 1990).

According to the discussion in Section 3.2, there are two FRs with two CRs. Therefore, two tasks were determined: Task 1 for wrist extension and Task 2 for wrist coordination. Figure 3-1 illustrates this conceptual design further, where Task 1 is associated with FR1 yet will also affect FR2. This is further to say that the function of wrist coordination needs the function of wrist extension. However, since these two functions are at different stages (i.e., wrist extension functional loss happens at Stage 3 and wrist coordination functional loss happens at Stage 6), functional assessment for wrist coordination with Task 2 will not be affected by the wrist extension functional loss.

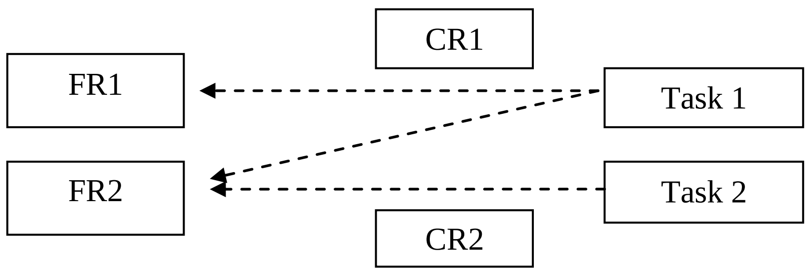

Figure 3-1: Conceptual design of the task for assessing wrist coordination functional loss at Stage 6 together with the task for assessing wrist extension at Stage 3 (dashed arrow line: correspondence of a task to a function)

The subsequent step of design followed FMA (Fugl-Meyer et al., 1975). The detailed guideline and principle of the test item at wrist in FMA can be found in Appendix B. In particular, for wrist extension, a task called "pass the tunnel" was designed based on the description of wrist extension (elbow 0 degree) in FMA. In this task, the patient is supposed to lift the virtual ball up in the tunnel by extending the wrist. Figure 3-2 further illustrates this task. For wrist coordination, a task called "Following a circle" was designed based on the test item called "wrist circumduction" in FMA. In this task, the patient is supposed to follow a circle by moving his or her wrist a round. Figure 3-3 further illustrates the "Following a circle" task.

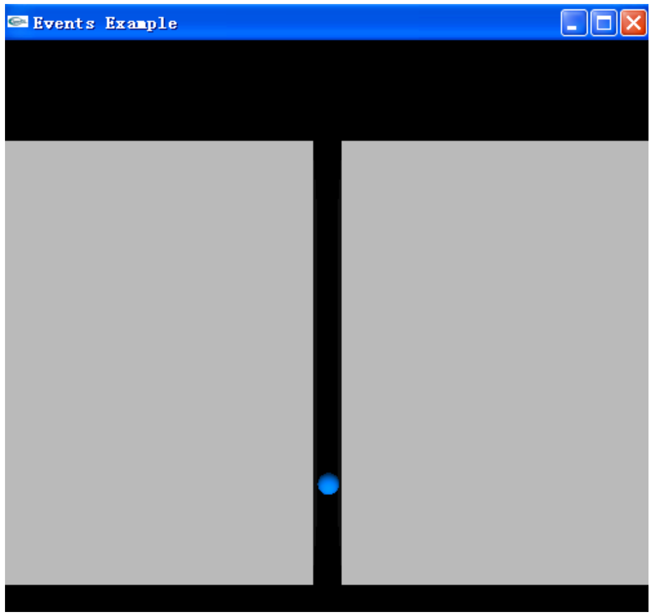

Figure 3-2: Task for wrist extension in the virtual environment

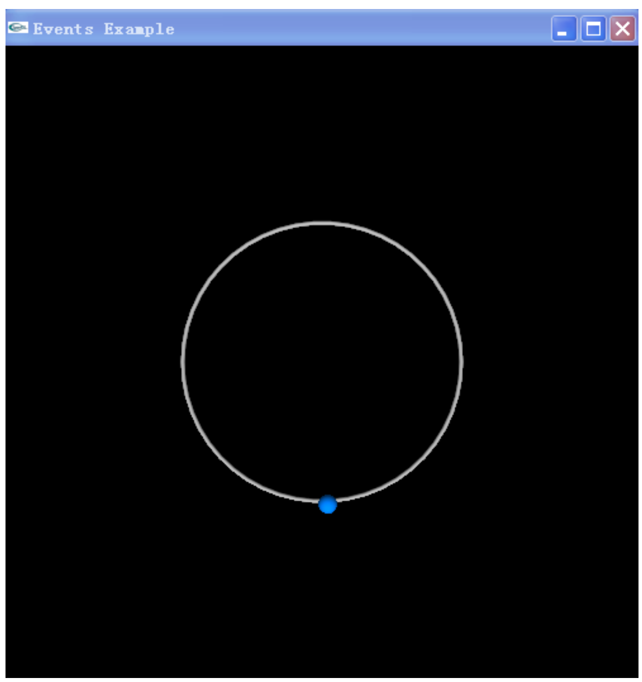

Figure 3-3: Task for wrist coordination in the virtual environment

3.4 Implementation

The foregoing conceptual design was implemented in a commercial package of the haptic device system. The implementation is described in this section. There is one issue in the implementation regarding the haptic device. Patients need to hold the haptic stick when they perform the tasks on the haptic system. In this study, it was assumed that the patients are at a recovery stage where they are able to hold the haptic stick. However, there is a need to develop functional assessment of “holding the haptic stick” in the future (See the future work in Chapter 6).

3.4.1 System set-up

The HVE system consists of a computer and haptic device (PHANTOM Omni) manufactured by the SensAble Technology. The computer provides a virtual environment, and it has a workspace of 160 (w) ×120 (h) ×70 (d) mm. Figure 3-4 illustrates the system setting of the HVE. In this figure, the haptic device plays a role as position input and force feedback from the virtual environment. At the beginning, users are supposed to move the haptic stick. At the end, they could see the virtual ball pointer moving in the screen and feel the sense of touch when the virtual ball interacts with other 3D objects in the virtual environment.

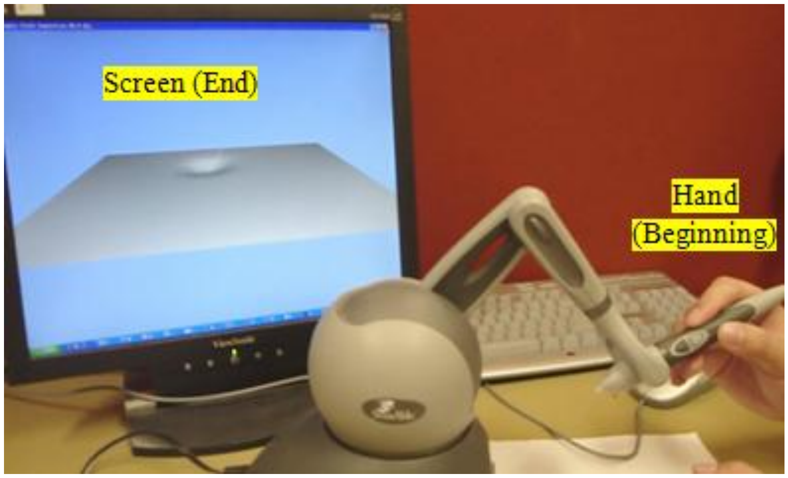

Figure 3-4: System setting of the haptic virtual environment (HVE)

3.4.2 Programming of tasks

This section presents the detailed programming to measure the kinematic motion performance in the virtual environment. The haptic software package provides the functions to construct a haptic virtual environment and to communicate it with the computer through IEEE 1394 interface. These packages can be found in the manual provided by the haptic device, namely, Programming Guide. The platform of the programming is in VC++. Figure 3-5 shows the flow chart of the program, which consists of three modules. The detailed code for realizing these modules is put in Appendix C.

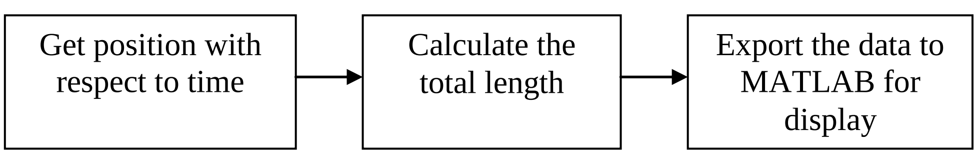

Figure 3-5: Flow chart of program for the measurement of task performance

The **first module** is to get position of the ball with respect to time. To get the position of the ball, the haptic software provides the function to get the position of the ball, namely, hduVector3Dd proxy. The VC++ has the library to get the time information, which allows getting task start time (t1) and task end time (t2).

The **second module** is to calculate the total length (s) of the movement of the ball. This is achieved with the following equation:

$$s = \int_0^T \dot{s}\,dt = \int_0^T \sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}\,dt \qquad (3\text{-}2)$$

where T refers to the total time of performing the task, $\dot{s}$ refers to the velocity of the virtual ball, and $\dot{x}, \dot{y}, \dot{z}$ refers to the velocity at x, y, z component, respectively. The sampling frequency of the haptic device is in the range of 50 Hz to 60 Hz. It was assumed that the sampling frequency is 60 Hz. Therefore, s is calculated by

$$s = \int_0^T \dot{s}\,dt = \sum_{t=1}^{n} \dot{s} \vartriangle t \qquad (3\text{-}3)$$

where$\vartriangle$ t refers to the inverse of sampling rate, n refers to the number of sampling points, which is equal to$\frac{T}{\vartriangle t}$. The x, y, z components of the velocity of the ball are calculated by

$$\dot{x}(t) = \frac{x(t+\vartriangle t) - x(t)}{\vartriangle t} \qquad (3\text{-}4)$$

$$\dot{y}(t) = \frac{y(t+\vartriangle t) - y(t)}{\vartriangle t} \qquad (3\text{-}5)$$

$$\dot{z}(t) = \frac{z(t+\vartriangle t) - z(t)}{\vartriangle t} \qquad (3\text{-}6)$$

where $\dot{x}(t)$,$\dot{y}(t)$, $\dot{z}(t)$represents the x, y, z component of the velocity, respectively.

The **third module** is to export the above calculations to the MATLAB environment for further data processing and display, which is straightforward.

3.4.3 Test procedure

Before the assessment, the patient should sit in front of the computer screen. The haptic device is positioned to the right or left side depending on upper limb (left or right) in assessment. The patient may be helped to set up the starting position by widgets (e.g., chairs, etc.). The test procedure with widgets is designed in the following:

For the **wrist extension task,** the starting position is with the wrist, and fingers are kept relax. The patient's arm should keep straight, while the elbow may be supported to achieve a required position. The support can be an elbow support with fastened on a box.

During the assessment, the constraint is that the operation is taken only with the wrist. The screen shot of the task is shown in Figure 3-2. The ball is placed at the bottom, and the patient is to manipulate the ball from the bottom up along the vertical tunnel until the ball is out. Figure 3-6 illustrate the wrist movement in wrist extension task.

Figure 3-6: Wrist movement in the wrist extension task

For the **wrist coordination task,** the starting position is with the wrist and fingers are kept relax. The patient's forearm is kept in such a way that the palm faces down, while the elbow is kept in flexion to 90 degrees. To keep the elbow in flexion to 90 degrees, the patient may have a support device on elbow which may be fastened on the widget. These constraints on elbow or arm ensure that the operation is taken only with the wrist. The screen shot of task is shown in Figure 3-3. During the assessment, the patient is required to move the hand round with the wrist only to follow a circle trajectory as displaced on the screen in the virtual environment. Figure 3-7 illustrate the wrist movement in the wrist coordination task.

Figure 3-7: Wrist movement in the wrist coordination task

It is noted that the scope of this thesis research is not to implement the design of widgets and supports for improving the aforementioned constraints. The conceptual design of widgets and supports is considered as a future work to be discussed in Chapter 6.

3.4.4 Measurement of patient's task performance

In the haptic virtual environment system, task performance is measured in the virtual environment. For "Pass the tunnel" task, the performance is the displacement of the ball in y-axis in the tunnel, which gives an indicator for the motion range of the wrist extension. For "Following a circle" task, the error between the actual trajectory of the ball and the desired trajectory is the performance, denoted by R. The R value gives an indicator to the functionality of a patient's wrist coordination. To compute R, the following parameters are measured:

- Position of the ball with respect to the starting point, (x, y, z);
- Time of the task performing (T);
- Perimeter of the circle (L) actually generated by the patient.

From these parameters, the trajectory (s) generated by the patient can be found by

$$s = \int_0^{\mathrm{T}} \dot{\mathrm{s}}\, \mathrm{dt} = \int_0^{\mathrm{T}} \sqrt{\dot{\mathrm{x}}^2 + \dot{\mathrm{y}}^2 + \dot{\mathrm{z}}^2}\, \mathrm{dt} \tag{3-7}$$

R is then calculated by

$$R = \left| \frac{\int_0^{\mathrm{T}} \dot{\mathrm{s}}\, \mathrm{dt}}{\mathrm{L}} - 1 \right| \tag{3-8}$$

The computer code for the above calculation is put in the Appendix C.

3.5 Evaluation

The whole haptic device system as built above is supposed to provide the performance indices to the therapist. The relation between the performance data and the level (well, partially, and fail) of the functional of a patient's upper limb can be either established by the therapist's visual inspection or established by some computing technique such as classifier. To develop such a classifier, there is a need of many samples, i.e., patients who perform the test on the developed system. This was unfortunately not done due to the scared resource available for this research. However, one patient subject was found from the City Hospital of Saskatoon. The patient was at Stage 6. Therefore, a preliminary evaluation of the effectiveness of the developed system for functional assessment was carried out.

According to the description from the occupational therapist, there was a deficit with this patient in his wrist coordination. In this case, the patient was invited to perform the "Follow a circle" task. A couple of healthy subjects were invited to do the same task, and their performances were recorded as control samples. The evaluation was simply done by comparing the patient performance data with the control. In the following, the entire experiment is described.

3.5.1 Hypothesis and assumptions

A hypothesis was proposed to compare the patient with the control (healthy subjects) of their performance data. The performance data in "Follow a circle" is the error (R) between the actual trajectory of the ball and the desired trajectory (See the detailed description of R in Section 3.4.4). The R for that stroke patient is 0.35 in the task. The **hypothesis** is that the average R of the healthy subjects is significantly lower than the 0.35 in the task of "Follow a circle".

The **assumptions** of the experiment are: (1) the samples were randomly selected from the population, and (2) the population from which the sample is drawn is normally distributed.

3.5.2 Material and method

3.5.2.1 Human subjects

A total of 8 healthy subjects (4 men, 4 women) were randomly selected from the students in the University of Saskatchewan. The age of the subjects is from 22 to 27 years old, and their ethnic identification is equal with 50% Caucasian and 50% non-Caucasians. All the healthy subjects were normal in both their physical and mental state. The result of power analysis will be presented by Section 3.5.3 to give some idea about the appropriateness of sample size.

3.5.2.2 Experiment procedure

The experiment was conducted as follows. For each subject, he or she was tested for two times. Before the experiment, the subject kept at the starting position for the assessment, as described in Section 3.4.3. Figure 3-8 shows the required position before the experiment. After the subjects completed the task, their task performance of information was represented by numbers for statistical analysis.

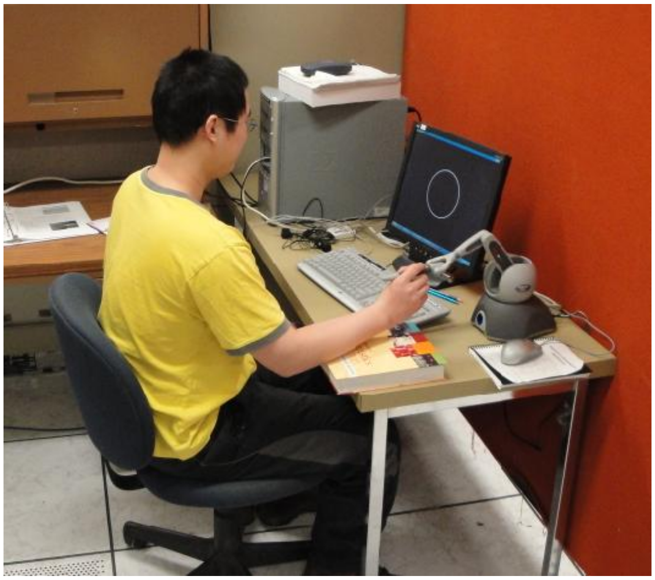

Figure 3-8: Required position before the experiment

3.5.2.3 Data acquisition

The data acquisition is to acquire the performance information of the subjects, including the actual trajectory of the ball and the error between the actual trajectory and predefined trajectory in the HVE system. This was achieved by Equation (3-5) and Equation (3-6) discussed in Section 3.4.

3.5.2.4 Data analysis

One-sample T test was employed to test the hypothesis, as the problem is to compare one-sample of the patient with the estimated average in the healthy subjects. The experiment was carried two times on the healthy subjects. The software of SPSS was employed to analyze the data. The significance level is α=0.05.

3.5.3 Results and discussion

First, power analysis was carried for the determination of the appropriate sample size. Rosner (2006) provided sample-size estimation for one sample test by

$$N = \frac{\sigma^2(z_{1-\beta}+z_{1-\alpha})^2}{(\mu_0-\mu_1)^2} \tag{3-9}$$

where σ represents variances, $1-\beta$ is the statistical power, α stands for significant level, $\mu_0, \mu_1$is the expected distance between one sample and population mean, and z represents normal distribution. Usually, the statistical power of the experiment in human behavior should be higher than 80% (Cohen, 1988). According to Equation (3-9), the number of 4 samples was found as the minimum sample size to achieve the power of 80% at a 5% significant level. In this experiment, 8 samples were employed to test hypothesis, and therefore a sufficient sample size was achieved. The statistical power is calculated by (Rosner, 2006)

$$\text{Power}= \phi[z_\alpha + \frac{(\mu_0-\mu_1)}{\sigma}\sqrt{n}] \tag{3-10}$$

where σ represents variances, α stands for the significant level, μ_1, μ_2 is the expected distance. Table 3-1 shows the descriptive statistics for the samples in order to calculate the statistical power of the experiment.

Table 3-1: Descriptive statistics for the samples in healthy subjects

	N	Mean	Std. Deviation	Std. Error Mean
First_time	8	.0725	.05970	.02111
Second_time	8	.1075	.04652	.01645

Based on the descriptive statistics shown in Table 3-1, the statistical power was calculated for the experiment: both of them are 100%, which is good enough to carry the experiment in human behavior.

Second, the test statistics and the corresponding p-value for the hypothesis are shown in Table 3-2:

Table 3-2: Illustration of p-value in the one-sample T test

	Test Value = 0.35					
					95% Confidence Interval of the Difference	
	T	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
First_time	-13.147	7	**.000**	-.27750	-.3274	-.2276
Second_time	-14.743	7	**.000**	-.24250	-.2814	-.2036

From Table 3-2, it can be seen that the difference in the both tests between the healthy subjects and the patient is significant (p-value<0.001).

Third, the result of test statistics is discussed in the form of graphical representation. Figure 3-9 displays a 95% confidence interval for the estimated average R of healthy subjects. From the figure, it can be seen that the average error for both trials by healthy subjects is significantly lower than the error (0.35) of the patient. Therefore, it is possible that the estimated average error among healthy subjects is significantly lower than the one of the patient at Stage 6.

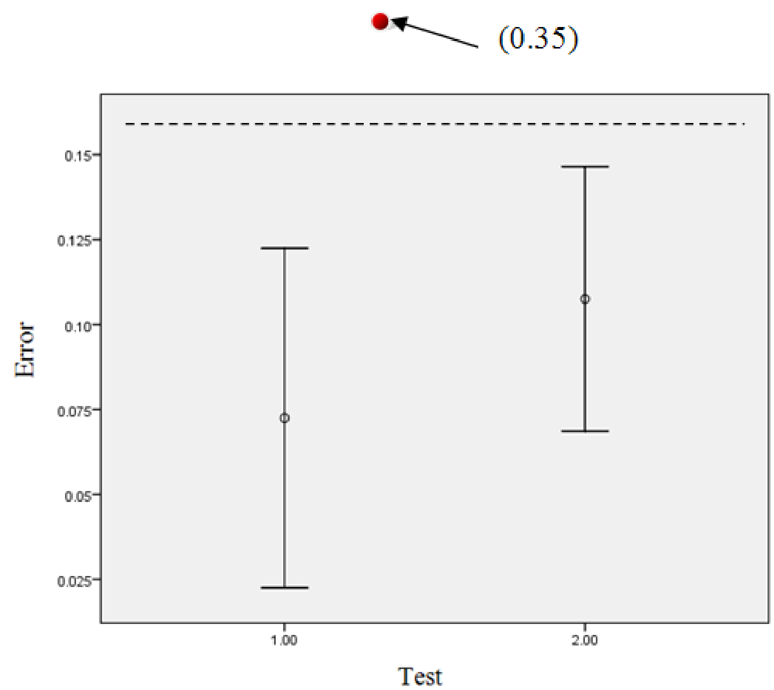

Figure 3-9: Estimated average error for both tests by healthy subjects

Last, the performance degradation between the patient and healthy subjects is discussed. To demonstrate the performance degradation, we compared the trajectory of the virtual ball in HVE generated by the patient with the one generated by the healthy subject. Figure 3-10 shows the patient's generated trajectory along the circle in the haptic system. This figure demonstrates that there is a saw-toothed trajectory representing jerk motions in the movement. Figure 3-11 illustrates the trajectory of the healthy subject, which is smoother than the one by the patient.

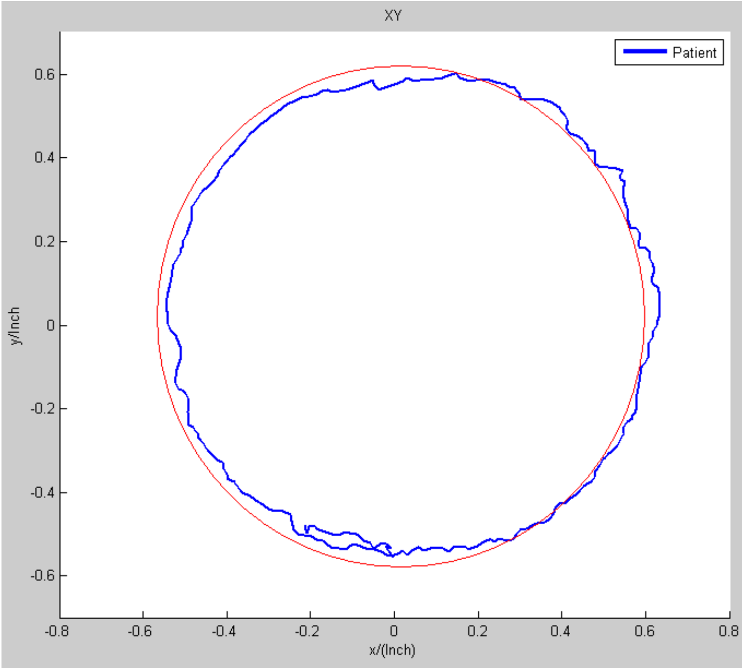

Figure 3-10: Trajectory of the patient in HVE (R=0.35)

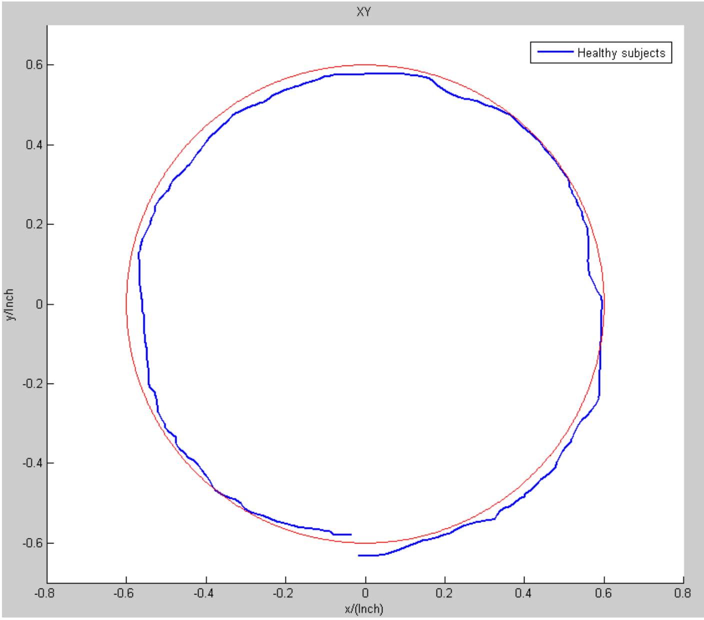

Figure 3-11: Trajectory of a healthy subject in the HVE (R=0.06)

3.6 Conclusion

The use of ADT allows us to have a systematic representation of how design parameters of the HVE system meet the requirements. This study demonstrates how to determine tasks and how to perform them in HVE in a systematic way. The present design was successful, as the task enables to differentiate the patient's task performance and the healthy subject's task performance. By comparing the present design with that of Bardorfer et al. (2001), the present design has the following advantages: (1) simple and straightforward task, (2) daily activity routine task, and (3) clear function specificity.

It is felt that the design of Bardorfer et al. (2001) is rather ad-hoc; for example, there was not any stage concept in their development, while the stage concept is practiced by clinicians. In fact, task design is affected by the stage concept, especially types of function loss at a particular stage. For instance, the task for wrist coordination at Stage 6 will be different from the one for wrist coordination at Stage 3. In this case, the design of task here for the wrist coordination at Stage 6 is upon the assumption that wrist extension is fine, and this point makes sense of a decoupled task design strategy as proposed in the above.

Chapter 4 Fatigue Inference

4.1 Introduction

Human mind states can only be inferred by cues. An inference system is to map cues to cognitive or emotional states. This thesis study was aimed at building a fatigue inference system with the cues of physiological signals. Since there is no first principle available for such a mapping from the physiological signals to fatigue, training data are always needed for learning towards the establishment of such a mapping. The purpose of this chapter is to describe a proposed approach to building the fatigue inference system. The validation of this approach will be presented in Chapter 5. Section 4.2 discusses the training data for the fatigue inference system. Section 4.3 presents a new approach to building the fatigue inference system. Section 4.4 discusses the implementation procedure to build the fatigue inference system. Section 4.5 presents a conclusion.

4.2 Training data to infer fatigue

There are three kinds of training data: physiological signals, task performance and subjective ratings. This section discusses the advantage and disadvantage of each of them with respect to the problem this thesis study concerned. The fatigue inference system developed in this thesis does not involve human decision makers in a decision loop. This is to say, there is no need of human decision based on the fatigue stage information, which means the label of fatigue can well go with a number system without involvement of any word. Therefore, the fatigue label taken in this study was simply a task performance when a human performs the task under a certain level of fatigue including the no-fatigue state. In other words, the score of task performance serves as a surrogate of fatigue. In doing so, the training data can have a much higher degree of objectivity; thereby, the accuracy of the inference expects to be improved. An example of word-based rating scale can be found in Appendix D. Though in the RSME scale, the output is a number, generation of this number first goes to the word interpretation of a fatigue state. It is noted that using words as the fatigue label will nonetheless improve the semantics of fatigue (semantics is defined as meaning in human mind); however, the process from the word of fatigue to number information will introduce a layer of subjectivity. The training data employed in thesis is presented as follows.

4.2.1 Physiological signal

Physiological signals collected in this study were heart rate variability (HRV) and skin conductance (SC). The following illustrates the connection between these physiological signals and fatigue in literature.

HRV differs significantly with respect to different fatigue states. The power spectrum of HRV contains 3 components: low frequency (LF), very lower frequency (VLF), high frequency (HF) (Bronzino et al., 2000). Oron-Gilad and David (2001) pointed out that there is a significant decrease in the LF/HF ratio from a normal state to a fatigue state. Further, Lin and Cai (2009) used a clustering method to extract the features to fatigue in the Electrocardiography (ECG) signals including LF/HF feature. Their study has shown that the LF/HF ratio had a strong correlation with the fatigue state. Therefore, the LF/HF ratio was employed in developing our fatigue inference system.

Skin conductance is a measurement of the electrical conductivity between the two points of the skin. Lang (1995) reported that skin conductance linearly correlates to arousal and reflects both emotional responses and cognitive activities. Previous studies

(Healey, 1999; Collet, 2003; Mehler et al., 2009) showed that there was a strong correlation between mental workload and skin conductance response in the context of driving. Since fatigue was elicited by time-varying mental workload in this thesis, skin conductance was employed to infer fatigue in this study.

4.2.2 Task performance

It is well known that fatigue is caused by a cyclic cognitive load on the mind system. The task performance approach is to produce a cyclic cognitive task to the human. In this study, the PASAT was employed as the cognitive task to generate the task performance. Cook et al., (2007) found that there is a general reduction in the percentage of correct response (PCR) in the PASAT due to a sign of fatigue. The performance score is the percentage of correct response (PCR) in the range of [0, 100].

4.2.3 Subjective rating

In this study, the subjective rating was used as the information to validate the inference system. The validation of the inference system is to correlate the performance score with the subjective rating. The correlation is to examine the consistency between the task performance and inherent interpretation of fatigue from human. In this case, the Rating Scale Mental Effort (RSME) developed by Zijlstra (1993) was employed. The rating score consists of 100 point scales that refer to several aspects of fatigue. The detailed questionnaire to acquire the subjective rating is presented in Appendix D.

4.3 Architecture of the inference system

The general methodology to build an inference system is to construct an input-output model by a mapping from cues to fatigue state. This study proposed a new approach to build the inference system. The architecture of the proposed inference system is shown in

Figure 4-1. The architecture has three layers. The **first** layer is a group of physiological signals, namely, HRV and skin conductance denoted by Cue 1 and Cue 2, respectively. The cues can be obtained from one individual or a group of individuals. The **second** layer is the algorithm based on machine learning formalism to map the cues to fatigue. An artificial neural network (ANN) was employed as a technique to provide such a machine learning process for such a mapping. The **third** layer is the inferred fatigue in the form of the performance score.

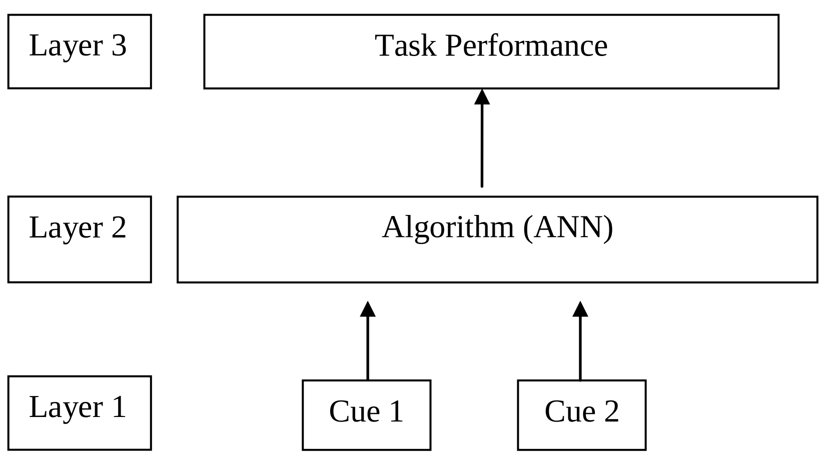

Figure 4-1: Architecture of the proposed inference system

Figure 4-2 illustrates the architecture of ANN. The architecture of ANN consists of the input-output pair and hidden layers. In this thesis, the input and output pairs the physiological signals and the performance score. The hidden layer consists of unknown layers and unknown neurons in each of them. The routes of mapping from input to output across these layers are called weights. The detailed description to determine the weights will be presented in Section 4.4.

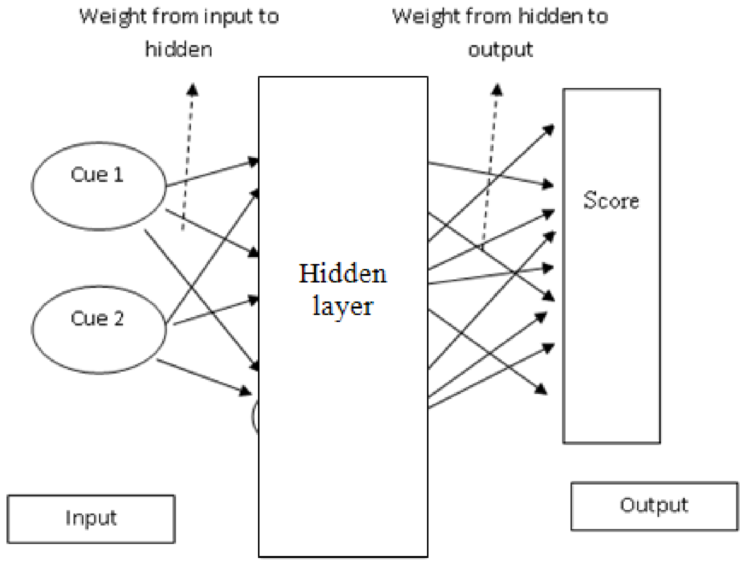

Figure 4-2: Structure of the artificial neural network (ANN)

4.4 Procedure

Figure 4-3 illustrates a general procedure to build the fatigue inference system, which is described as follows:

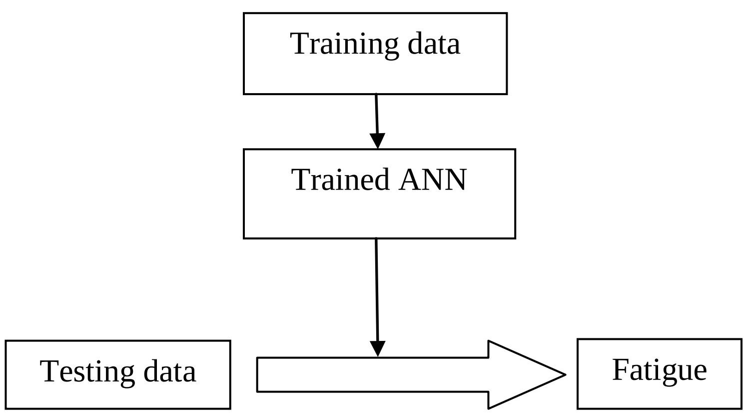

Figure 4-3: General procedure to build the fatigue inference system

Step 1: Establish a training data set

In this thesis, the training data consists of the physiological signal and performance score. The training data can be gathered from one individual or a group of individuals. In this study, both individual training data and group training data were acquired for the purpose of comparison of them (see objective 3 of this study, described in Chapter 1).

It is noted that the raw data has to be preprocessed before it can serve as training data. For physiological signals, the difference between the raw data and the baseline data in the relaxed condition is calculated in order to minimize the bias that comes from the environment and bad signals. Further, the physiological signals and the performance score need to be normalized to the range of [0, 1] for a neural network. This study followed the method of minimum-maximum (min-max) normalization to constrain the raw data. Priddy and Keller (2005) pointed out that the min-max normalization has the advantage of preserving exactly all relationships in the data and it does not introduce any bias. They further presented min-max normalization as

$$x' = \frac{x - min_{value}}{max_{value - min_{value}}} \quad (4\text{-}1)$$

where $\mathrm{min}_{\mathrm{value}}$ and $\mathrm{max}_{\mathrm{value}}$ stands for the value of minimum and maximum in raw data, respectively.

Step 2: Apply a training algorithm to determine the weights

Once the training data set is established, the network is ready for training. Training is a process to determine the weights. In this study, a feed-forward training algorithm called back propagation algorithm was employed to determine the weights. The back propagation (BP) algorithm is a well known algorithm to generate weights in a neural network. Hecht-Nielsen (1989) presented the basic theory of the BP algorithm. Figure 4-4 illustrates the schematic of BP to train the ANN. The methodology is to start from random weights in the mapping and compare the output with an error. Before BP is carried out to train the ANN model, there are several elements of ANN to be determined: input and output layer, the number of layers and the number of neurons in each of the hidden layers, training time and speed. The input and output layers of the training data have been established in Step 1. In this study, it was assumed that there was 1 hidden layer and 3 neurons in that layer. In addition, the author defined the iteration time and rate, namely 10000 and 10 (Hz), respectively. In this study, MATLAB was employed to train the ANN. The detailed description of the procedure to train ANN in MATLAB is presented in Appendix E.

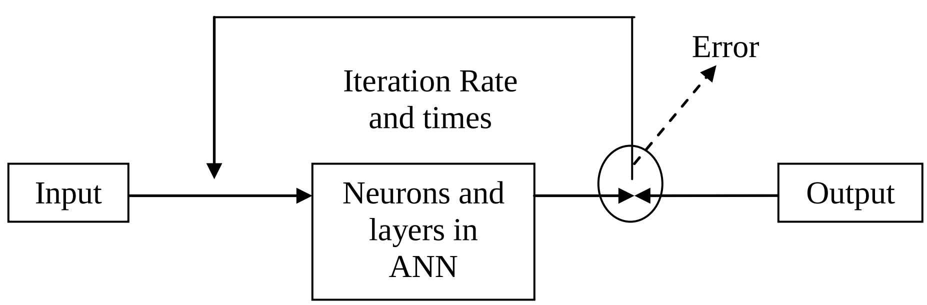

Figure 4-4: Schematic of the BP to train ANN

Step 3: Test the accuracy of the ANN model

After the ANN is trained, the weights are determined. The inference system is ready to predict the performance score based on the cues of fatigue. The accuracy of ANN model is examined from the errors between the predicted score and actual score. The testing result will be presented in the validation of the inference system described in Chapter 5 - in particular Section 5.4.1.

4.5 Conclusion

This chapter presented a new fatigue state inference approach, which is, using physiological signals as cues and task performance score as a surrogate of the fatigue. This new approach is expected to achieve an improved accuracy, which will be validated in Chapter 5. Note that this new approach is suitable to any application where human decision making is not needed.

Another pilot effort with this inference system is on understanding individual-based inference versus group-based inference. The individual-based approach builds the inference system upon the cues of fatigue on individuals rather than the average cues across individuals. The individual-based approach may significantly contribute to improvement of the accuracy of the inference system. The current literature has not provided knowledge regarding the difference between the individual-based inference and group-based inference. Chapter 5 will conduct an experiment to examine such difference.

Chapter 5 Experiments for Fatigue Effects

5.1 Introduction

This chapter is devoted to experiments towards an understanding of the fatigue effect on human task performance in the haptic virtual environment system as described in Chapter 3. Due to limited resources, the experiment could not be performed by patients but was only performed by healthy subjects. It should be noted that the intended experiments are made possible by the two developments which were described in Chapter 3 and Chapter 4, respectively, namely a haptic virtual environment system for the assessment of wrist coordination in Chapter 3 and the proposed inference system to infer the fatigue state in the context of rehabilitation in Chapter 4. This chapter is organized in the following. Section 5.2 will discuss the hypothesis and assumption for the experiments, followed by a description of the design of experiments in Section 5.3. Section 5.4 will present results along with discussion, including the verification of the fatigue inference system described in Chapter 4. Section 5.5 will conclude this chapter.

5.2 Hypothesis and Assumption

Two hypotheses were proposed:

Hypothesis (1): The elevated fatigue state will significantly affect the assessment of the upper limb function of the healthy subjects in the haptic virtual environment system.

For stroke patients, the assessment of their upper limb function is task-oriented. Motor behaviors are implicitly represented by task performance. If the result in the healthy subjects is such that the performance-based assessment is not only contributed by motor behavior but also an elevated fatigue state, the result should likely be valid to patients.

Hypothesis (2): The individual-based inference is significantly more accurate than the group-based inference in the fatigue state inference for healthy subjects.

Humans are quite individualized, which may cause significant errors in inferring an individual's mind state based on a group-based learning. The concept of the individual-based inference was first proposed by Lin (2006) and was studied in this thesis study.

There were several **assumptions** for underlying the experiments:

1) The participants are in no-fatigue state prior to the experiment.

2) The populations follow normal distribution.

3) The populations have the same variance.

5.3 Data acquisition and data analysis

5.3.1 Factor and response

This study only considered two fatigue states: non-fatigue state (control) and significant-fatigue state. The factors with their levels and responses for the experiments are defined as follows:

For hypothesis (1), there are two factors and one response. One factor is fatigue state. It has two levels: Level 1: no-fatigue (used as control treatment) and Level 2: significant-fatigue. Due to possible inconsistent interpretation across individuals, this study analyzed fatigue factor as within-subjects factor. The other factor is the day when the rehabilitation task is performed. It has two levels corresponding to two time spans of days for rehabilitation task performing. The response is the rehabilitation task performance, which was intended to evaluate a patient's upper limb function. Section 5.3.4 presents the detailed description of the rehabilitation task performance.

For hypothesis (2), there are only one factor and one response. That factor is the inference model. It has two levels: Level 1: individual-based inference and Level 2: group-based inference. The response is the accuracy of the inference model. Section 5.3.3 presents the detailed description of the fatigue inference model. Further, Section 5.4.1 discusses the accuracy of the model.

5.3.2 Participants

A total of 8 participants (4 men, 4 women) were randomly selected from the students in the University of Saskatchewan. The subjects were 22-27 years old, and their ethnic identification was equal with 50% Caucasians and 50% non-Caucasians. All the subjects are healthy in both their physical and mental states. The relevant power analysis will be presented in Section 5.4.

5.3.3 Elicitation of Fatigue

The experiment requires stimuli that can elicit fatigue. The goal of the elicitation in the experiment is to elicit two levels of fatigue, namely, no-fatigue and significant-fatigue states. **No-fatigue state** is used as a control treatment. **Significant-fatigue state** is caused by a cyclic workload in mental effort. Figure 5-1 illustrates the schematics of the fatigue elicitation. The figure shows that the significant-fatigue state is caused by the time-varying workload in great mental effort. In this study, PASAT was employed to elevate the fatigue state. For **no-fatigue state**, the subjects did the PASAT task for one trial with 3 minutes; for **significant-fatigue state**, the subjects did the task, which consists of five 3-minute on-trials and followed by 1-minute off-trials. In this study, it is assumed that the subjects are in no-fatigue state prior to the experiment. The validation of fatigue elicitation is presented in Section 5.4.2.

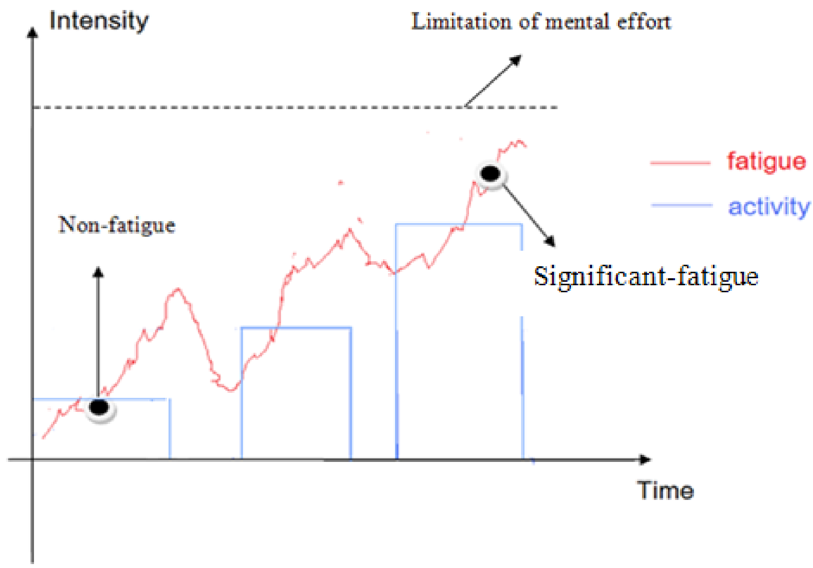

Figure 5-1: Schematic of fatigue elicitation

5.3.4 Fatigue inference

The methodology and procedure to build the fatigue inference system are referred to Chapter 4. This section presents the way to get the training data and the relevant instrumentation to be used for data acquisition.

5.3.4.1 Physiological signals

Physiological signals collected in the experiment were heart rate variability (HRV) and skin conductance (SC). To get the training data of HRV and SC, 8 participants were asked to participate in the experiment. The individual-based inference model was set up for each individual and each of them was tested for 20 times including 16 times of training and 4 times of testing. In this study, the sensing system called ProComp 2 developed by Thought Technology Ltd was employed for signal acquisition and processing. The ProComp 2 provides 2 channels to connect the sensors, and they were connected with blood volume pulse (BVP) sensor (which is to further come up with HRV) and SC sensor. Figure 5-2 illustrates show how the sensor probes connect to humans.

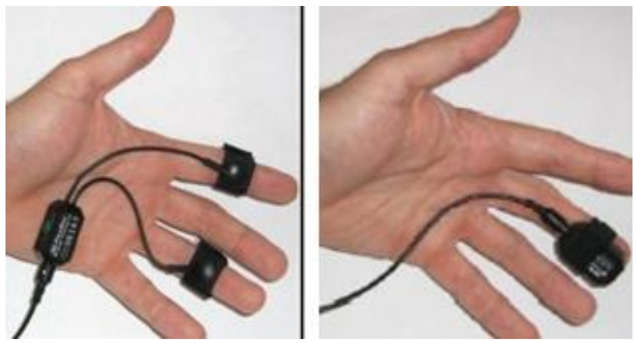

Figure 5-2: SC sensor (left side) and BVP sensor (right side) developed by Thought Technology Ltd (http://www.thoughttechnology.com/sensors.htm)

It is noted that the sensing system also includes software, called BioGraph Infiniti, to extract the relevant features (e.g., LF/HF ratio) from the raw physiological signals. The sampling rate of BVP and SC are 256 Hz and 32 Hz, respectively. Figure 5-3 illustrates the acquisition of raw BVP signals and extraction of HRV features with the software. Figure 5-4 illustrates the acquisition of raw SC signals.

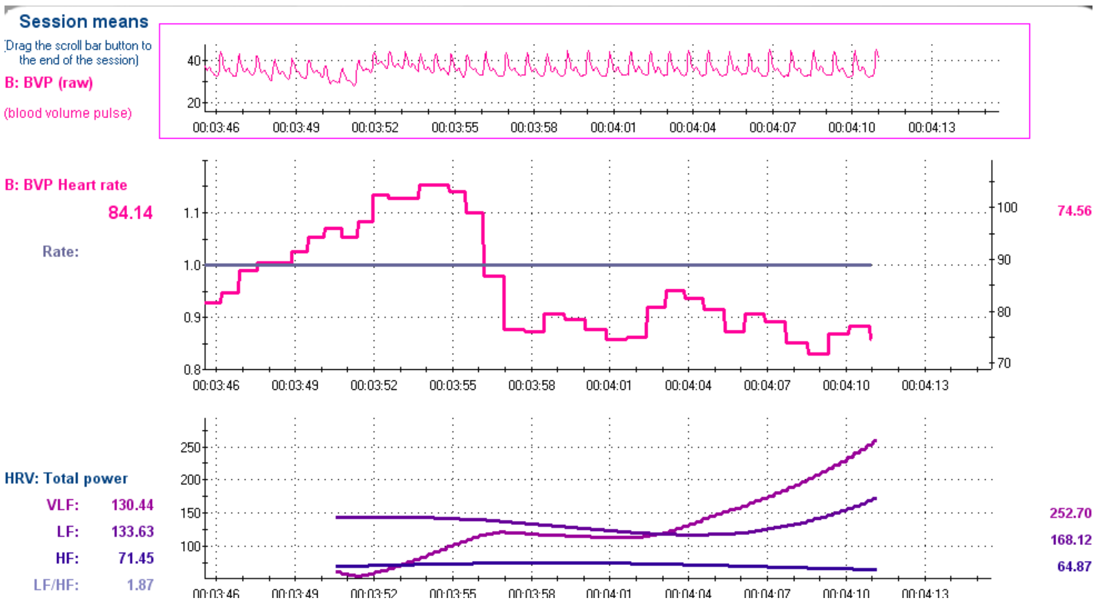

Figure 5-3: Acquisition of raw BVP signals and extraction of HRV features

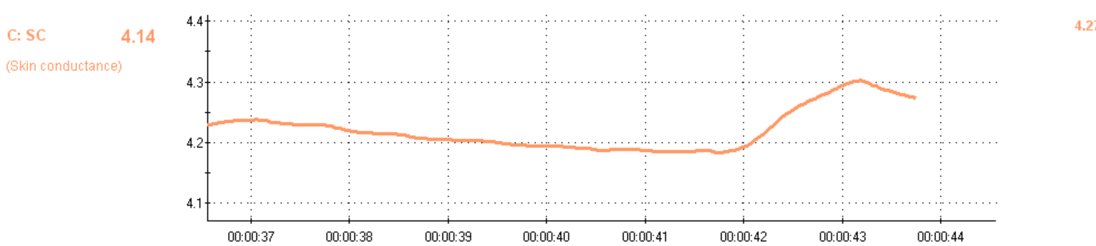

Figure 5-4: Acquisition of raw SC signals

5.3.4.2 Task performance

As stated elsewhere in Chapter 4, a general approach taken in the experiment to infer the fatigue state was performance-based, i.e. task performance score serving as a surrogate of fatigue. The cognitive task was carried out online in the website called Cognitive fun. Figure 5-5 illustrates the interface for the subjects to do the PASAT.

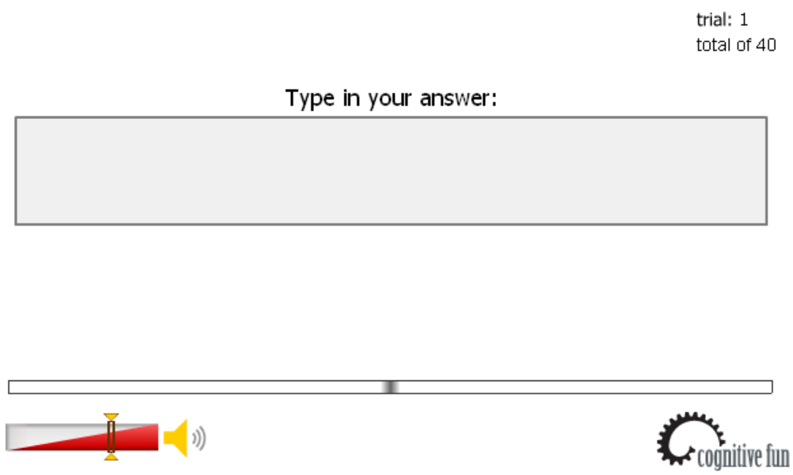

Figure 5-5: Interface for the PASAT (http://cognitivefun.net/test/25)

5.3.5 Rehabilitation task performance

The performance data is the error (R) between the actual trajectory of the ball and the desired trajectory (See the detailed description of R in Section 3.4.4). The parameter (R) is further normalized by

$$\text{Normalized performance} = \frac{Original\ (R)}{Baseline\ (R)} \quad (5\text{-}1)$$

where the original R represents the raw performance data, and baseline R represents the average R when the subjects are in no-fatigue state. The normalized performance represents a degree of the change in task performance from no-fatigue to significant-fatigue state.

5.3.6 Experiment procedure

This study has been approved by the Ethics Committee in the University of Saskatchewan to carry out the experiment. The certificate of approval is attached in

Appendix F. For each subject, there were two stages in the experiment. The first stage was to train the artificial neural network (ANN), and the second stage was to infer the fatigue state based on the cues or signals. Figure 5-6 illustrates the general procedure to carry out the experiment.

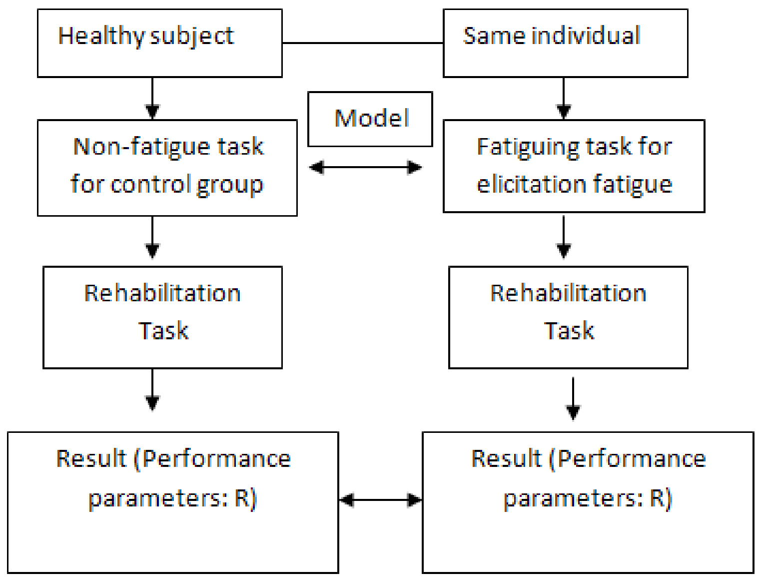

Figure 5-6: General procedure of the experiment

In the first stage, each subject was tested for 16 times (8 times for no-fatigue and 8 times for significant-fatigue). The experiment for the first stage was carried out for 16 times in 8 days in total. At each day, the subjects did the PASAT to elicit the fatigue state with two levels corresponding to no-fatigue (used as control treatment) and significant-fatigue states. During the task performing, the physiological signals were measured. Following the task immediately, the subject filled out the questionnaire to rate their feeling of mental fatigue state. In this study, it took seconds to fill out the questionnaire for the subjects. At the end, the subjects worked on the rehabilitation task.

In the second stage, testing data was collected to infer the fatigue state, and then the rehabilitation task was performed. The participant was tested for 4 times in the second stage (2 times for no-fatigue and 2 times for significant-fatigue). The subjects performed the PASAT tasks to elicit their no-fatigue and significant-fatigue state. The following procedure is the same as the one in the first stage.

It is noted that each subject in the experiment performed the tasks several times. The familiarity may become a factor, as the subject may develop a strategy based on the experience of performing a previous task to execute the current task. Therefore, the performance of the current task may be influenced by such an experience, which then compromises the assumption that each task performing is independent of any previous task performing. In the design of the experiment, the subjects perform two tasks in different times which have a sufficiently long time span (seven days in this case).

5.3.7 Data analysis

First, the power analysis was carried out to determine the required sample size. Rosner (2006) presented a sample-size estimation method by

$$N=\frac{(\sigma_1+\sigma_2)^2(z_{1-\beta}+z_{1-\alpha})^2}{(\mu_1-\mu_2)^2} \qquad (5\text{-}2)$$

where σ_1, σ_2 represent variances for two population, $1-\beta$ is the statistical power, α stands for significant level, $\mu_1, \mu_2$is the expected distance between the two population mean, and z represents normal distribution. Cohen (1988) pointed out that the statistical power of the experiment in human behavior should be higher than 80%. According to Equation 5-2, 8 people with proper repeated measurements are sufficient to achieve the power of 80% using a 5% significant level.

Second, data analysis is presented for each hypothesis. The significant level α is equal to 0.05 for the experiments conducted in this thesis. **For hypothesis (1)**, the randomized block ANOVA test was employed as the test method, because there were several treatments to affect rehabilitation performance in each block, namely, the subject in the experiment. Table 5-1 shows rehabilitation performance in terms of four treatments to combine fatigue and day variables in the blocks, namely, 7 subjects in the experiment. In this case, the assumption for ANOVA test is valid that the blocks are independent with each other.

Table 5-1: Rehabilitation performance in randomized block design

	Block 1	Block 2	……	Block 7
No-fatigue and Day 1	0.85	0.64		0.50
Sig-fatigue and Day 1	1.00	2.18		2.50
No-fatigue and Day 2	0.77	0.82		0.33
Sig-fatigue and Day 2	1.46	1.09		2.33

For hypothesis (2), the paired sample T test was employed as the test method, because there was only one factor (methods of inference in this case) in the experiment.

5.4 Results and discussion

The result is presented in three parts. The first part provides the validation of the inference system, which has been outlined in Chapter 4. In the first part, the validation of inference examines the error of the inference model and the correlation between the fatigue measurement and subjective rating. The second part presents the result of **power analysis** for the both hypothesis. The third part presents the results of **test statistics** for the both hypotheses.

5.4.1 Validation of the fatigue inference system

The accuracy of fatigue state inference is measured by two aspects. The first aspect is the error between the inferred fatigue and known fatigue. The second aspect is the correlation between the inferred fatigue and subjective rated fatigue. It is to be noted that the label of the fatigue in this study was task performance score and the label of fatigue using the subjective rating technique is the RSME scale (Zijlstra, 1993), which is given in Appendix D.

Table 5-2 provides the results of the accuracy of the approach developed in this study with a comparison of the accuracy of some others' studies in the literature. From this table it can be seen that the approach developed in this study is the best in terms of accuracy. It is noted, however, that the number of levels of a mind state can affect the accuracy of inference. Therefore, a further comparison of the inference system developed in this thesis with other is needed in future. There are further a couple of remarks regarding the accuracy of the approach developed in this study. **Remark 1**: An individual-based inference strategy was used in the approach developed in this study.

Table 5-2: Result of accuracy of fatigue inference

Study	Training data	Measurement	Accuracy	
			Error	Correlation
(Picard et al., 2001)	EMG, SC, EKG	8 categories of emotion with each having two levels	81%	N/
(Nasoz et al., 2004)	SC, HR, ST	6 categories of emotion with each having two levels	71%	N/
(Lin and Cai, 2009)	ECG	Mental workload with four levels	N/	0.85
(Shen et al., 2008)	EEG	Mental fatigue with 5 levels	87.2%	N/
This study	SC, HR	Mental fatigue with 2 levels	**89.54%**	**0.753**

Remark 2: The actual task performance score was acquired from the subjects in their second part of the test, as described before. **Remark 3**: The error is further calculated by $\frac{1-error}{1} \times 100\%$. Further, the accuracy **89.54%** calculated from the error is the average accuracy from 7 (instead of 8) subjects. Among the 8 subjects, the largest error is in Subject #1 (accuracy=58%), while the smallest error is in Subject #5 (accuracy=99%). Figure 5-7 further illustrates the accuracy of the fatigue inference among the 8 subjects. In the figure, “0” stands for no-fatigue, while 1 stands for significant-fatigue.

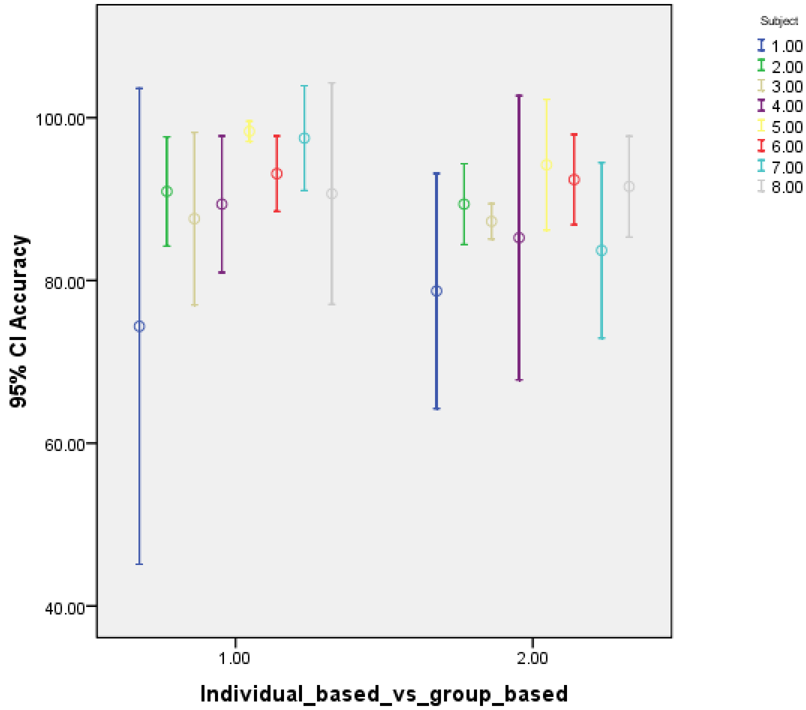

Figure 5-7: Accuracy of the fatigue inference model among 8 subjects

Table 5-3 shows the descriptive statistics of accuracy of mind state inference. According to Table 5-3, the accuracy x should be satisfied by $\overline{x} - 2\sigma < x < \overline{x} + 2\sigma$ to achieve a higher statistical power. In this case, the error of the inference in the Subject #1 is extremely distinct from the others, so this subject has not been considered in the data analysis for this study.

Table 5-3: Descriptive Statistics of accuracy of mind state inference

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Accuracy	64	58.51	99.93	89.0216	8.82066	77.804
Valid N (listwise)	64					

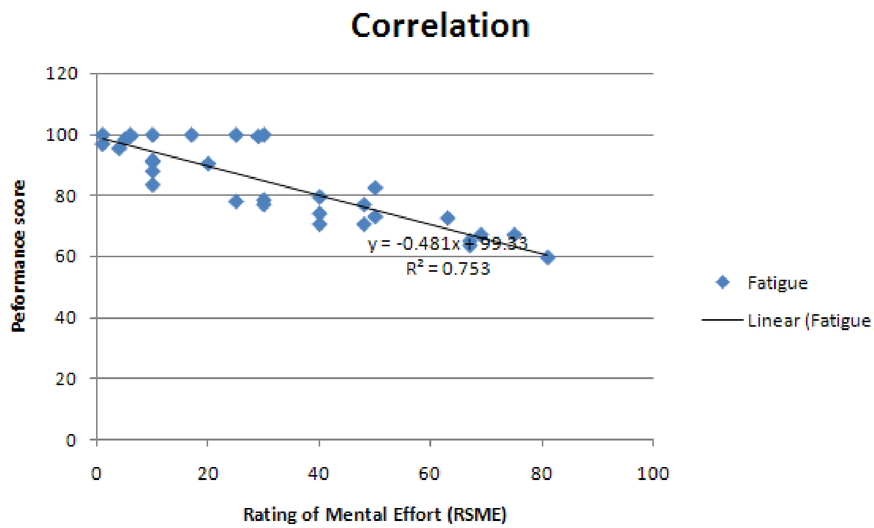

Figure 5-8: Scatter plot between the performance score and subjective rating

Figure 5-8 shows the scatter plot that describes the correlation between the inferred fatigue which is based on the PASAT task performance score and subjective rating which is based on RSME. From this figure it can be seen that the task performance score is linearly related to the subjective rating. As such, the Pearson's analysis was further carried out to examine the correlation. Table 5-4 shows the Pearson correlation coefficient=0.875. Therefore, at the 5% level of significance, there is a significant correlation between the fatigue measurement (i.e., task performance) and subjective rating **(p-value<0.001)**. This result raises the confidence in the proposed fatigue inference approach, and at the meantime this implies that the subjective rating measure is reliable to the particular application problem this study is concerned.

Table 5-4: Correlation between the fatigue measurement and subjective rating

		Subjective_rating	Measured_score
Subjective_rating	Pearson Correlation	1	**-.875****
	Sig. (2-tailed)		.000
	N	28	28
Measured_score	Pearson Correlation	**-.875****	1
	Sig. (2-tailed)	.000	
	N	28	28

**. Correlation is significant at the 0.01 level (2-tailed).

5.4.2 Validation of fatigue elicitation

In order to validate the fatigue elicitation, a statistical analysis was conducted to compare fatigue measurement in terms of no-fatigue and significant-fatigue. Table 5-5 presents the T-test result for this comparison. From Table 5-5: T-test statistics is: t (13, 0.05) = 8.274, corresponding to p-value < 0.01. Therefore, at the 5% significant level, there is evidence to conclude that there is a significant difference in fatigue measurement between no-fatigue and significant-fatigue (p-value<0.01).

Table 5-5: T-test statistics of fatigue measurement in terms of fatigue

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	Significant_fatigue - No_fatigue	.49357	.22321	.05966	.36469	.62245	8.274	13	.000

Figure 5-9 further illustrates the result in Table 5.5. In this case, the fatigue state takes two values, 0 and 1. In particular, 0 means that participants are not fatigue at all, and 1 means that participants are extremely fatigue. From Figure 5-9 it can be seen that the level of measured fatigue in significantly or extremely fatigue is significantly higher than the one in no-fatigue state.

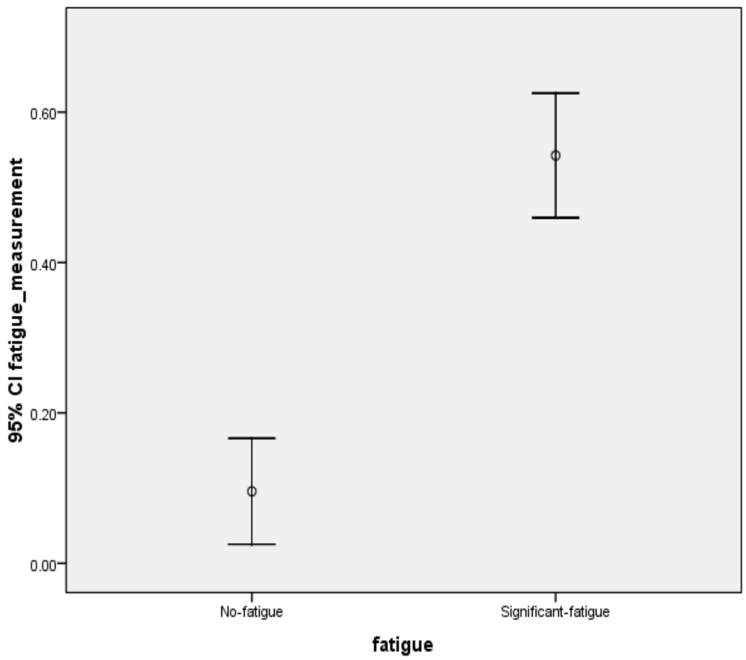

Figure 5-9: Fatigue measurement in terms of no-fatigue and significantly-fatigue

5.4.3 Result of power analysis

To calculate the statistical power, the descriptive statistics were employed to get the average, standard deviation, and sample size. The following presents the descriptive statistics for the both hypotheses: For **hypothesis (1)**, Table 5-6 shows the descriptive statistics of the rehabilitation performance data in terms of fatigue.

Table 5-6: Descriptive statistics of rehabilitation performance

	N	Mean	Std. Deviation
No_fatigue	14	.8679	.37026
Significant_fatigue	14	1.6007	.67552
Valid N (listwise)	14		

For **hypothesis (2)**, Table 5-7 shows the descriptive statistics of fatigue measurement in terms of fatigue. Based on the descriptive statistics, the statistical power is calculated by (Rosner, 2006)

$$\text{Power}= \phi[-z_{(1-\alpha)/2} + \frac{(\mu_1-\mu_2)}{\sigma}\sqrt{n}] \tag{5-3}$$

where σ represent average variance of two populations, α stands for significant level, $\mu_1, \mu_2$is the expected distance. Based on the descriptive statistics, the statistical power was calculated for the both hypotheses: the statistical power = 93.4% and 84.96%, respectively. The statistical power is higher than 80%, which is strong enough to carry out the designed experiments.

Table 5-7: Descriptive statistics of fatigue inference

	N	Mean(accuracy)	Std. Deviation
Individual-based	28	92.50	4.96
Group-based	28	88.39	5.36
Valid (List wise)	28		

5.4.4 Result of test statistics

This section presents the result of the test statistics for the both hypotheses. **For Hypothesis (1)**: Table 5-8 shows the F-test statistics and corresponding p-value for the randomized block design. From Table 5-8: F-test statistics is: (1) for the treatment variable, F (6, 21) = 3.739, corresponding to p-value = 0.03; (2) for the block variable, F (6, 21) = 0.634, corresponding to p-value = 0.702. Table 5-9 shows the result of the post-hoc analysis of treatments, namely, day and fatigue variable on rehabilitation performance. From Table 5-9: F-test statistics is: (1) for the day variable, F (6, 21) = 0.169, corresponding to p-value = 0.686; (2) for the fatigue variable, F (6, 21) = 11.045, corresponding to p-value = 0.004.

Table 5-8: Test statistics of treatments and blocks

Tests of Between-Subjects Effects

Dependent Variable:Rehab_Performance

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Treatment	Hypothesis	3.937	3	1.312	3.739	.030
	Error	6.319	18	.351[a]		
Block	Hypothesis	1.336	6	.223	.634	.702
	Error	6.319	18	.351[a]		

a. MS(Error)

Table 5-9: Test statistics of treatments on the rehabilitation performance

Tests of Between-Subjects Effects

Dependent Variable:Rehab_Performance

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Fatigue	Hypothesis	3.877	1	3.877	11.045	.004
	Error	6.319	18	.351[a]		
Day	Hypothesis	.059	1	.059	.169	.686
	Error	6.319	18	.351[a]		
Fatigue * Day	Hypothesis	.001	1	.001	.002	.965
	Error	6.319	18	.351[a]		
Block	Hypothesis	1.336	6	.223	.634	.702
	Error	6.319	18	.351[a]		

a. MS(Error)

For hypothesis (2), Table 5-10 shows the T-test statistics and corresponding p-value. From Table 5-10, the test statistics of T-test = 2.467, corresponding to p-value = 0.02.

Table 5-10: Test statistics in accuracy between individual-based and group-based

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	Individual_based - Group_based	3.39789	5.28880	1.37745	.57159	6.22419	2.467	27	.020

5.4.5 Discussion

This section discusses results for the both hypotheses. For the **first hypothesis** (fatigue effect on rehabilitation)**,** at the significance level α=0.05, there is no evidence to conclude that measurements in different subjects affect the rehabilitation performance for the assessment in the healthy subjects with F (6, 21) = 0.634, corresponding to p-value = 0.702. The post-hoc analysis of different treatments on rehabilitation performance shows that there is no significant variance in rehabilitation performance between two days of measurement. However, there is evidence to conclude that there is significant difference in rehabilitation performance for the assessment of wrist coordination between no-fatigue state and significant-fatigue state in the healthy subjects with F (6, 21) = 11.045, corresponding to p-value = 0.004. This result indicates that fatigue significantly affects rehabilitation performance in the HVE.

Figure 5-10 displays a 95% confidence interval for the estimated average error (R) with respect to the baseline performance in terms of fatigue. Figure 5-10 shows that fatigue affects the performance in wrist coordination significantly. In addition, at the significant-fatigue state, the error in significant-fatigue state can increase up to 2 times as much as the error with respect to no-fatigue state.

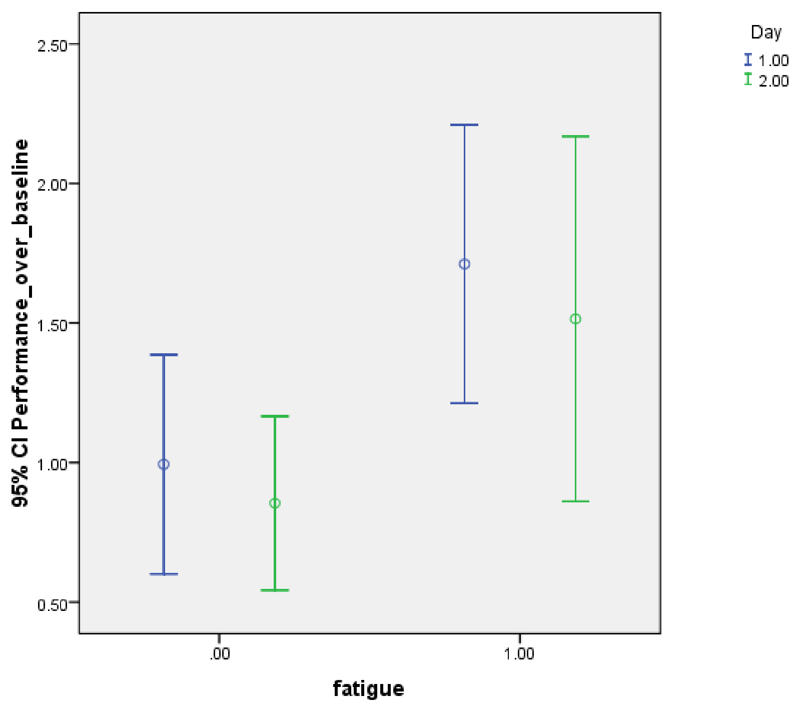

Figure 5-10: Estimated average error(R) with respect to the normal condition between no-fatigue (left) and significant-fatigue (right)

For the **second hypothesis** (individual-based vs. group-based), at the 5% level of significance, there is evidence to conclude that there is a significant interaction between subject and fatigue states in the fatigue inference with T-test statistics = 2.467, corresponding to **p-value = 0.02**. Therefore, it can be concluded that there is significant difference in the accuracy of the inference approach between the individual-based and group-based inferences. Figure 5-11 further displays the accuracy between the individual-based and group-based inference among the 7 subjects and shows that there is a general decrease in accuracy from individual-based inference to group-based inference among 7 subjects.

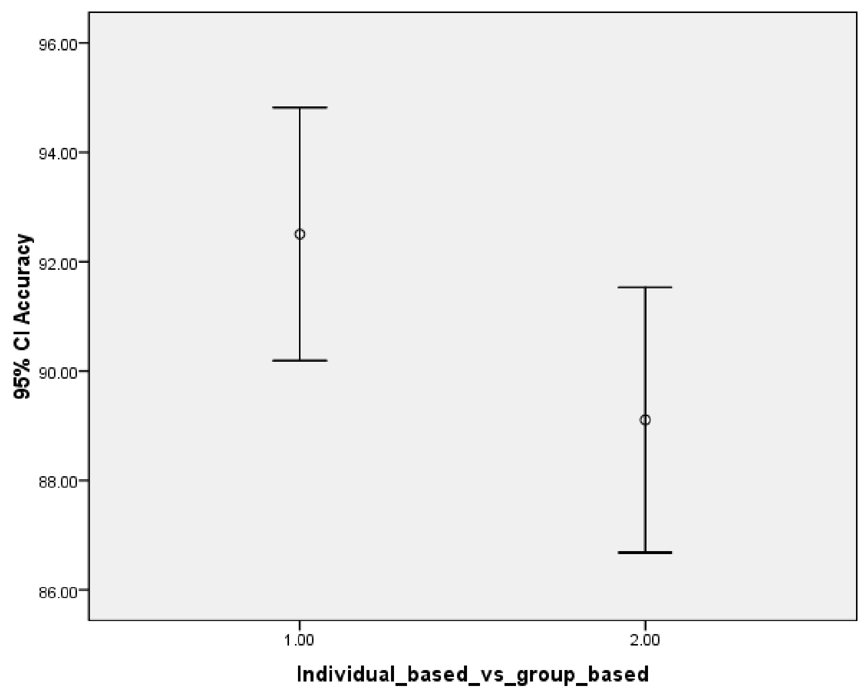

Figure 5-11: Accuracy in individual-based and group-based inference

5.5 Conclusion

The experiments were described in this chapter. The experiments were to test the two hypotheses which are further related to the two objectives (objective 2 and objective 3) described in Chapter 1. The first hypothesis was to examine the fatigue effect on the rehabilitation task performance for functional assessment of upper limb, in particular wrist coordination. It can be concluded from the result that an elevated fatigue state significantly affects the wrist coordination task performance in the context of rehabilitation.

The second hypothesis was to investigate the difference between the individual-based inference and group-based inference. It can be concluded from the result that the accuracy of the individual-based inference is significantly higher than that of the group-based inference. The underlying reason for this conclusion is believed to connect with inherent differences among individuals of human beings. However, the individual-based inference approach needs a large size of training data on one “particular” individual, which usually takes a longer period of time. In the group-based inference, training data are across a group of individuals, which are usually gathered in a shorter period of time.

Chapter 6 Conclusion and Recommendations

6.1 Overview

This thesis described a study on fatigue effect on task performance in the context of rehabilitation. The study was motivated to quantify the fatigue effect on functional assessment of the affected upper limb and focused on the haptic virtual environment approach to rehabilitation. The general methodology for this study was experimental-based and took a rational design approach to build up a haptic virtual environment (HVE) system and to develop a fatigue inference system. The experiments followed the statistic-based approach.

The thesis is composed of six chapters, covering the motivation of the study, questions to be answered, objectives of the study, design of the haptic virtual environment system, design of the fatigue inference system, and the experiments for two hypotheses (hypothesis I: the elevated fatigue state will significantly affect functional assessment of upper limb for healthy subjects in the HVE system; hypothesis II: the individual-based inference is significantly more accurate than the group-based inference in fatigue state inference for healthy subjects).

6.2 Conclusions

1) The HVE presents its great potential for functional assessment of upper limb in the home-based rehabilitation approach. The HVE quantifies the rehabilitation task performance for the assessment of wrist coordination. The accuracy of the HVE is comparable to the clinic practice commented by therapists.

2) It is promising to apply ADT to design HVE systems for rehabilitation. With ADT, the HVE can be designed for high task specificity in the context of functional assessment of upper limb. The design of Bardorfer et al. (2001) is rather ad-hoc (e.g., there was not any stage concept in their development). This study has demonstrated that the HVE for the functional assessment of wrist coordination is effective in that the task enables to differentiate task performance between the patient and the healthy subject.

3) It is promising to use task performance as a surrogate of fatigue for the inference system that excludes human decision makers in a decision loop. Due to a higher degree of objectiveness of the physiological signal and task performance score, the fatigue inference system developed based on the physiological signal and performance score can achieve higher accuracy. The inference result is also consistent with that by the subjective measurement approach, especially of the RSME scale.

4) In the context of rehabilitation, the elevated fatigue state will significantly affect task performance. Though this conclusion is derived from the healthy subjects, it is quite likely that the conclusion is valid to patients.

5) The accuracy of individual-based inference is significantly higher than that of the group-based inference. Though this conclusion is derived from the healthy subjects, it is quite likely that the conclusion is valid to patients.

6.3 Contributions

1) This study has provided a platform for the systematic design and testing of tasks in HVE for functional assessment of upper limb. For instance, this platform can be easily extended to functional assessment of wrist extension of stroke patients.

2) This study has generated the knowledge about the fatigue effect on rehabilitation task performance. The procedure for generating this knowledge can be extended to knowledge for other mind states such as anxiety and so on.

3) This study has generated the knowledge to understand the difference between individual-based inference and group-based inference – in particular the former is much accurate than the latter.

6.4 Limitations and Future work

This thesis presents a primary experimental study on fatigue effect in the healthy population. Future work should focus on the feasibility of the experiment on the patient population. There are some issues that need to be addressed, and they are discussed in the following:

First, it is necessary to develop a new assessment system to ensure that patients are capable of holding the haptic stick. One possible approach is to employ non-intrusive force sensors to measure the strength of the fingers to hold the stick. It is noted that, for the patients at lower recovery stages, their main function loss is to stretch their fingers. To hold the stick is not easy until Stage 5.

Second, there is a need to develop an accessory device to enforce the correct posture in doing functional assessment of upper limb with the HVE system developed in this thesis study. The device should be simple and easy to use; as otherwise, the device may be a factor to reduce the patient’s motivation to perform rehabilitation. Figure 6-1 shows a conceptual design of such a device for functional assessment of wrist coordination. In the figure, the accessory hoops built upon the widget are to constrain the forearm and elbow so that any movement can only be initiated from the wrist.

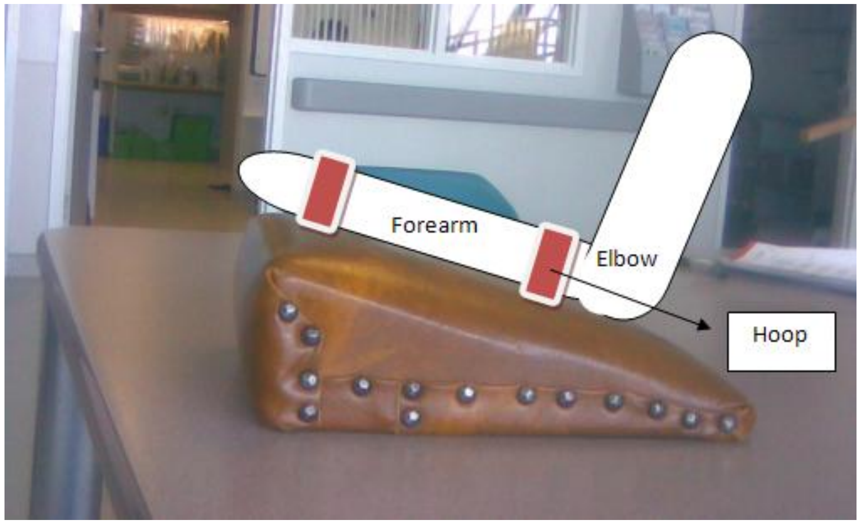

Figure 6-1: Example of design to a simple support device for constraints

Third, there is a need to develop non-intrusive sensors on the haptic device to acquire physiological signals to infer the fatigue state. The current paradigm for such sensors is natural-contact sensor proposed by Lin (2011). There are several requirements of the natural-contact sensors: (1) the size of sensors is ideally in micro-scale or nano-scale, (2) the sensing system should be flexible enough in order to be applied to curved surfaces on the haptic device, and (3) the signals should be characterized in an array integrated with multiple sensor channels (such as heart rate, skin conductance, and gripping force). Figure 6-2 shows a prototype of a flexible 32×32 sensing system integrated with tactile sensors, developed by Kim et al. (2009). In the figure, the size of the sensor unit is 1 mm× 1mm and the overall sensing module size is 5.5 cm × 6.5 cm.

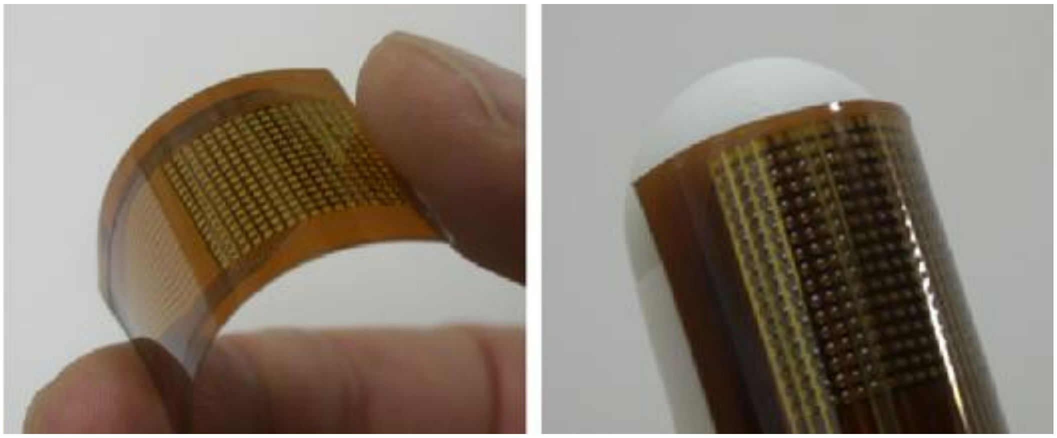

Figure 6-2: Flexible sensing system proposed by Kim et al. (2009)

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Appendix A: Detailed Description of Axiom Design Theory (ADT)

Axiomatic design theory (ADT) was proposed by Suh (1990). ADT provides a systematic approach to develop a system that satisfies functional requirements (FRs) and constraints. Design parameters (DPs) satisfy the specific FRs. ADT is based on two design axioms: the Independence Axiom and the Information Axiom. In this study, the first axiom is briefly introduced, as it is relevant to this thesis:

Axiom 1: The Independence Axiom-Maintain the independence of the FRs

The ideal design decision in Axiom 1 is always be made without violating the independence of each function requirement from the other functional requirements. The FRs are defined as the minimum sets of independent requirements that characterize the design goals. The design of Axiom 1 is the mapping process from FRs to DPs. During the mapping process, all possible different ways of satisfying the FRs need to be considered by identifying reasonable DPs called conceptualization process considering all available methods such as brainstorming, morphological techniques, analogy from other examples, extrapolation and interpolation, law of nature, order-of-magnitude analysis, and reverse engineering. A design equation that describes the relation between the two vectors can be expressed mathematically as

$$\{\mathrm{FR}\} = [\mathrm{A}]\{\mathrm{DP}\} \tag{A-1}$$

where [A] is called a design matrix that characterizes the product design. A design matrix for a design that has nFRs and nDPs is expressed as

$$[A] = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{11} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix} \tag{A-2}$$

If a design matrix [A] is a full matrix which is neither diagonal nor triangular, a design cannot satisfy the independence axiom, which is called a '**coupled design**'. The matrix [A] must be either diagonal or triangular in order to satisfy the independence axiom. Each of the FRs can be satisfied independently with one DP if the design matrix [A] is diagonal, which is called an '**uncoupled design**'. If the design matrix is triangular, the independence of FRs can be assured if only if the DPs are determined in an appropriate sequence, which is called '**decoupled design**'.

Appendix B: Guideline of Test Item in Fugl Meyer Assessment (FMA)

This section presents the test item for wrist function in Fugl Meyer Assessment (FMA) developed by Fugl-Meyer (1975). The right column shows an ordinal scale with degradation in performance.

2. Wrist

2.1 Wrist stability (elbow 90°) Apply resistance at 15° dorsiflexion. The elbow may be supported if needed. *Lift your hand and hold it there, keep your elbow bent.*	15° Dorsiflexion cannot be performed 0 Dorsiflexion performed but not against resistance 1 Position can be maintained against slight resistance 2
2.2 Wrist flexion/extension (elbow 90°) The elbow may be supported if needed. *Lift your hand up and down, keep your elbow bent.*	No voluntary movement 0 Voluntary movement but not through total passive range 1 Movement through total passive range 2
2.3 Wrist stability (elbow 90°) Apply resistance at 15° dorsiflexion. The elbow may be supported if needed. *Lift your hand, hold the position with your arm straight.*	15° dorsiflexion cannot be performed 0 Dorsiflexion performed but not against resistance 1 Position can be maintained against slight resistance 2
2.4 Wrist flexion/extension (elbow 90°) The elbow may be supported if needed. *Lift your hand up and down with your arm straight.*	No voluntary movement 0 Voluntary movement but not through total passive range 1 Movement through total passive range 2
2.5 Wrist circumduction *Move your hand around, keep your elbow bent and your arm still.*	Movement cannot be performed 0 Jerky motion or incomplete circumduction 1 Detail performed fully and adequately 2

Appendix C: Detailed Programming

This section presented the detailed programming is HVE.

The time of user performing the task is equal to (t2-t1). See the detailed programming as follows:

```
{  t1 =GetTickCount();//Getting the system time before the test(ms)
   std::cout <<"Begin to test"<< std::endl;
 }


{  t2=GetTickCount();//Getting the system time after the test(ms)
t3= (t2-t1)/1000; //time of perform the test
   std::cout <<"Test is over"<< std::endl;
 }
```

To get the position of the virtual ball, we used the package of calibration in the virtual environment. The detailed programming is presented as follows:

```
hduVector3Dd proxy;
        hlCacheGetDoublev(cache, HL_PROXY_POSITION, proxy);
 std::cout <<"Position of ball pointer: "<<proxy[0]<<" "<<proxy[1]<<" "<<proxy[2]
```

The detailed programming to calculate the total length of the ball movement is presented in the following:

```
{          dt=16.67;    //sampling (ms)
```

```
x[m]=proxy[0];//Get the x,y,z position
  y[m]=proxy[1];
z[m]=proxy[2];


        xv[m]= (x[m]-x[m-1])/dt;//Get the x,y,z velocity
     yv[m]= (y[m]-y[m-1])/dt;
zv[m]= (z[m]-z[m-1])/dt;
sumtest=sumtest+sqrt(pow(xv[m],2)+pow (yv2[m],2)+ pow (zv2(m),2))*dt;
//Get the trajecotry
}
```

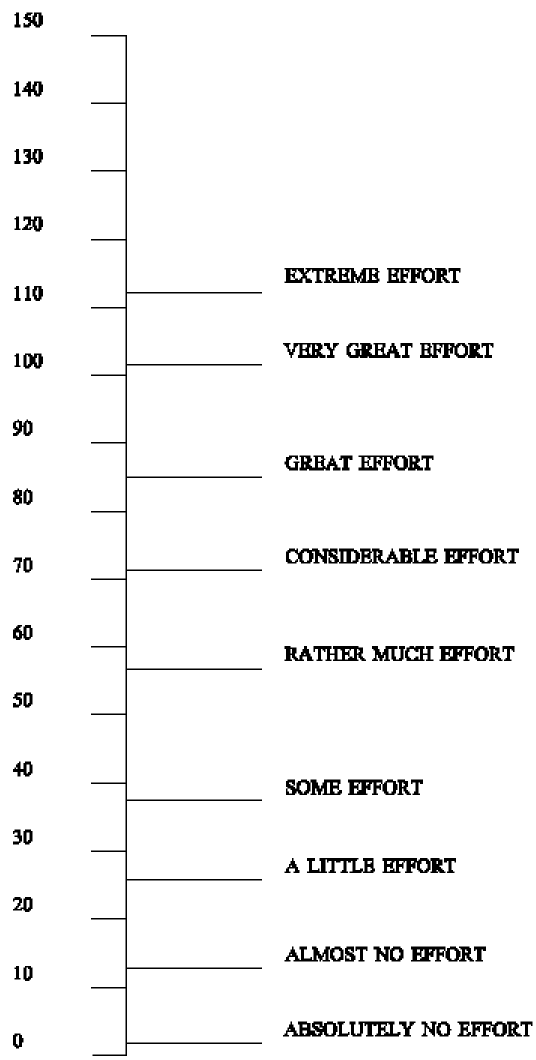
The detailed programming to get graphical results in Matlab is presented in the following:

```
axisequal
axis([-0.8,0.8,-0.7,0.7]);
holdon
plot(x(:,1),x(:,2),'LineWidth',2);
title('XY')
xlabel('x/(Inch)')
ylabel('y/Inch')
```

It is noted that x [1, 2] represents the position information in x, y coordination in the haptic virtual environment.

Appendix D: Rating Scale Mental Effort (RSME)

The appendix is RSME developed by (Zijlstra, 1993) for subjective rating for mental effort. The score is indicated by the digits on the left.



Appendix E: Train Artificial Neural Network (ANN) in MATLAB

This section presents the procedure and detailed programming to train ANN in MATLAB.

(1) Get the training data and input the data in excel file

For example, the train data is acquired as shown in the following: In the table, X1 and X2 is the input of the model, and Y is the output of the model:

X1	X2	Y
0.27	0	0.06
0.38	0.03	0.06
0.57	0.38	0.46

(2) Load the training data in a feed-forward training algorithm called back propagation (BP) in MATLAB

In this study, the original BP source code in MATLAB can be downloaded in the website: http://www.philbrierley.com/main.html?code/matlab.html&code/codeleft.html. The following is the source code to load training data by excel file:

```
M=xlsread('trainingData.xls');

train_inp(:,1)=M(:,1);
train_inp(:,2)=M(:,2);
train_out=M(:,3);
```

(3) Set the user defined parameters to determine the weight

The parameters should be defined in terms of the structure of ANN and training algorithms: number of neurons, rate of learning and number of iterations. The following is the source code to determine the weight of ANN:

```
hidden_neurons = 3;
epochs = 10000;
alr=0.1;
```

(4) Save the weight in excel files and test the accuracy of the model

The following is source code of saving weights and loading the model to test the accuracy in MATLAB:

```
% save the model
```

Input_hidden=xlswrite(‘input_hidden.xls’,weight_input_hidden);
Hidden_output=xlswrite(‘hidden_output.xls’,weight_hidden_output).

```
% Load the model

weight_input_hidden=xlsread('input_hidden.xls');
weight_hidden_output=xlsread('hidden_output.xls');

%Load the testing data

M=xlsread('testingData.xls');

train_inp(:,1)=M(:,1);
train_inp(:,2)=M(:,2);
train_inp(:,3)=1;

train_out=M(:,3);

pred = weight_hidden_output*tanh(train_inp*weight_input_hidden)';
```

Appendix F: Certificate of ethics approval for the experiment

UNIVERSITY OF SASKATCHEWAN

Behavioural Research Ethics Board (Beh-REB)

Certificate of Approval

PRINCIPAL INVESTIGATOR	DEPARTMENT	BEH#
Chris Zhang	Mechanical Engineering	11-61

INSTITUTION(S) WHERE RESEARCH WILL BE CONDUCTED
University of Saskatchewan

STUDENT RESEARCHER(S)
Chun Yang

FUNDER(S)
INTERNALLY FUNDED

TITLE
Effect of Elevated Fatigue on Task Performance in Upper Limb Function

ORIGINAL REVIEW DATE	APPROVAL ON	APPROVAL OF:	EXPIRY DATE
06-Mar-2011	22-Mar-2011	Ethics Application Consent Protocol	22-Mar-2012

Full Board Meeting ☐ Date of Full Board Meeting:

Delegated Review ☒ Expedited Review: ☐

CERTIFICATION

The University of Saskatchewan Behavioural Research Ethics Board has reviewed the above-named research project. The proposal was found to be acceptable on ethical grounds. The principal investigator has the responsibility for any other administrative or regulatory approvals that may pertain to this research project, and for ensuring that the authorized research is carried out according to the conditions outlined in the original protocol submitted for ethics review. This Certificate of Approval is valid for the above time period provided there is no change in experimental protocol or consent process or documents.

Any significant changes to your proposed method, or your consent and recruitment procedures should be reported to the Chair for Research Ethics Board consideration in advance of its implementation.

ONGOING REVIEW REQUIREMENTS

In order to receive annual renewal, a status report must be submitted to the REB Chair for Board consideration within one month of the current expiry date each year the study remains open, and upon study completion. Please refer to the following website for further instructions: *http://www.usask.ca/research/ethics_review/*

John Rigby

John Rigby, Chair
University of Saskatchewan
Behavioural Research Ethics Board

Please send all correspondence to:

Research Ethics Office
University of Saskatchewan
Box 5000 RPO University, 1602-110 Gymnasium Place
Saskatoon SK S7N 4J8